Consumer's Acceptance of Mobile Health Technologies in Germany

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Resumo

As equipas de administração da industria farmacêutica acreditam que a digitalização da saúde criará novos segmentos de mercado no futuro, enquanto que a saúde móvel propulsará mudança. Embora a adoção de tecnologias por parte de médicos tenha sido já extensivamente analisada no passado, pouco avanço tem sido feito na identificação de fatores que determinam a intenção de adotar tecnologias móveis de saúde pelos consumidores. Após uma extensiva análise de investigações anteriores, a presente tese adota a Teoria Unificada de Aceitação e Uso de Tecnologia, estendendo o modelo referido para incluir determinantes de utilidade negativa que possam impedir a adoção de tecnologias móveis de saúde pelos consumidores. O presente estudo concentra-se no mercado alemão e consequentemente, os dados recolhidos por meio de um questionário online dizem respeito a um total de 289 consumidores alemães. Os resultados obtidos através de uma analise PLS-SEM indicam que autoeficácia antecede expectativa de esforço, e que expectativa de desempenho, influência social, condições de facilitação e receio de monitorização são fatores determinantes na intenção de adotar tecnologias móveis relacionadas à saúde por parte dos consumidores. O presente estudo contribui desta forma para a atual investigação da aceitação de tecnologias moveis relacionadas com a saúde por parte de utilizadores no continente Europeu. Os resultados apresentados pretendem ainda constituir uma fonte de informação útil para gestores, profissionais de marketing ou criadores de tecnologias moveis ligadas à saúde, para que possam compreender melhor os fatores mais relevantes na aceitação destas aplicações por parte dos consumidores. Conclui-se que as características utilitárias das aplicações em questão devem ser realçadas, alinhando a sua promoção aos segmentos de mercado adequados e promovendo uma receção positiva pelos consumidores, o que conduzirá a uma maior aceitação de intenção de adotar tecnologias moveis ligadas a saúde.

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Abstract

Les cadres de l’industrie pharmaceutique attendent de la santé digitale qu’elle fasse apparaître de nouveaux segments de marché, et figurent que la santé sur téléphone mobile sera le vecteur de ce changement. Tandis que l’adoption de la santé mobile du point de vue physiologique a déjà été fréquemment étudiée, peu d’études ont cherché à identifier les facteurs déterminants de l’adoption de cette technologie de santé sur mobile par les consommateurs. Après une large revue de littérature, cette étude appliquera la ‘Unified Theory of Acceptance and Use of Technology’ (UTAUT) et étendra ce modèle aux concepts d'utilité négative qui pourrait empêcher l'adoption de cette technologie. Le marché allemand sera le domaine d’étude. Ainsi, des données issues de consommateurs allemands ont été récoltées grâce à un questionnaire en ligne (n=289). Les résultats tirés du PLS-SEM indiquent que la Self-Efficacy (auto efficacité) est un antécédent de l’Effort-Expectancy (effort attendu) et que les concepts de Performance Expectancy (performance attendue), Social Influence (influence sociale), Facilitating conditions (conditions favorables) et Surveillance Anxiety (anxiété de surveillance) affectent de manière significative l’intention d’adoption des technologies mobiles des consommateurs. L’étude apporte des éléments de recherche supplémentaires sur l’acceptation de la santé sur mobile par les utilisateurs européens. De plus, les résultats apportent des conclusions sur les déterminants de l’acceptation des technologies de m-santé utiles aux développeurs, aux marketeurs et aux managers du secteur de la santé sur mobile. Plus précisément, les paramètres utilitaristes des produits doivent être privilégiés tout en ciblant les early-adopters dans le but d’encourager le bouche-à-oreille qui, enfin, conduira à de plus fortes intentions d’adoption de ces technologies de santé sur mobile.

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Abstract

Executives within the pharmaceutical industry expect digital health to spur new business segments to action, while mobile health will serve as an activator for change. Whereas technology adoption from a physician's perspective has already been frequently examined, little has been done to identify factors that determine consumers' intention to adopt a mobile health technology. After an extensive literature review, this work adopts the Unified Theory of Acceptance and Use of Technology (UTAUT) and extends that model to include constructs of negative utility that might prevent adoption. The research setting is the German market, hence data from German consumers was collected through an online survey (n=289). Findings from a PLS-SEM indicate that Self-Efficacy is an antecedent of Effort-Expectancy, and that the constructs of Performance Expectancy, Social Influence, Facilitating Conditions and Surveillance Anxiety significantly impact consumer's intention to adopt m-health technologies. The study contributes to research on users' acceptance of mobile health on the European continent. Moreover, the results do provide m-health developers, marketers and managers with insights on what determines consumers' acceptance of these applications. In practical terms, the products' utilitarian features should be stressed and early adopters targeted, to foster word-of-mouth, which will ultimately lead to stronger behavioural intention of adopting m-health technologies.

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List of Abbreviations

AVE	Average Variance Extracted
BI	Behavioural Intention
CR-α	Cronbach's Alpha
EE	Effort Expectancy
FC	Facilitating Conditions
HBM	Health Belief Model
ICT	Information Communication Technologies
IDT	Innovation Diffusion Theory
m-health	Mobile health
PE	Performance Expectancy
PEOU	Perceived Ease Of Use
PLS	Partial Least Squares
PLS-SEM	Partial Least Squares Structural Equation Modelling
PMT	Protection Motivation Theory
PR	Physical Risk
PS	Perceived Privacy and Security Risk
PU	Perceived Usefulness
RFID	Radio-Frequency Identification
SA	Surveillance Anxiety
SCT	Social Cognitive Theory
SE	Self-Efficacy
SI	Social Influence
TAM	Technology Acceptance Model
TAM2	Extended Technology Acceptance Model
TPB	Theory of Planned Behaviour
TRA	Theory of Reasoned Action
UTAUT	Unified Theory of Acceptance and Use of Technology
UTAUT2	Extended Unified Theory of Acceptance and Use of Technology

1. Introduction

1.1 Problem Definition and Relevance

Emerging technologies and analytical tools will lead to a form of medicine that Hood and Friend (2011) coined as the ‘4P medicine’: Predicitive, Personalized, Preventive and Participatory. Through the wider dispersion of Information Communication Technologies (ICT), digital healthcare offerings like telemedicine, electronic health records and telecarehave emerged (Cho, et al., 2009). Roland Berger (2016) expects the value of digital health services and products to surpass USD 200bn by 2020, with mobile health technologies as the main driver for growth. Despite their predicted potential, Cho, et al. (2009) also comment that the typical life trajectory of a telehealth innovation often ends after initial funding – not because of the projects viability, but due to user’s resistance to use the technology. Kummer, et al. (2017) complement this view as they quote outright rejection and missing acceptance to be main reasons for failed market introductions of technologies. As a consequence, and "as technical barriers disappear, a pivotal factor in harnessing this expanding power of computer technology becomes our ability to create applications that people are willing to use" (Davis, et al., 1989, p. 982). Concluding, it is essential to investigate which factors drive users’ acceptance of a technology, and that – with the forthcoming digitalization – especially in the healthcare industry.

In literature, consumer’s health choices have most often been considered from behaviour change theories (e.g. Munro, et al., 2007) as well as from perspectives that investigate technology acceptance. The most prominent models that belong to the latter category are the Technology Acceptance Model (TAM) as well as the Unified Theory of Acceptance and Use of Technology (UTAUT) and their respective extensions. Albeit both have been frequently used in the healthcare context, UTAUT models tend to have a better validity in predicting consumer’s behavioural intention, typically ranging around 70% (Venkatesh, et al., 2003). While several researchers have already examined technology acceptance from a physician’s point of view (e.g. Bhattacherjee & Hikmet, 2007; Cho, et al., 2009; Yarbrough & Smith, 2007) or analysed the acceptance of Electronic Health Records (e.g. Angst & Agarwal, 2009), there exists limited research on consumer’s acceptance of m-health technologies as also Sun, et al. (2013) note. Further, most of the related research that has been empirically proven has been pursued on either the Asian (e.g. Gao, et al., 2015; Sun, et al., 2013; Lee & Han, 2015; Jen & Hung, 2010; Deng, et al., 2014) or the American continent (e.g. Cho, et al., 2014; Dwivedi, et al., 2016). Besides, it often either focused on a specific domain of m-health, as for example wearables (e.g. Gao, et al., 2015) or health apps (e.g. Cho, et al., 2014). Moreover, several studies have investigated technology's impact on patients adhering to a treatment of a specific illness, e.g. in a longitudinal study pursued by Cho, et al. (2009) investigating the diffusion of telehealth innovations for a telestroke program or Dwivedi, et al. (2016) studying m-health adoption by diabetic patients. Furthermore, most of the research has been carried out by examining the adoption behaviour of young consumers or students (e.g. Becker, 2016; Jen & Hung, 2010; Whetstone & Goldsmith, 2009). Eventually, Featherman & Pavlou (2003) criticise that most of the research that studies consumer's acceptance of e-services solely focuses on utility gains, thus perceived benefits, but much less so on utility losses, hence risks involved from embracing a technology.

1.2 Research Question and Objective

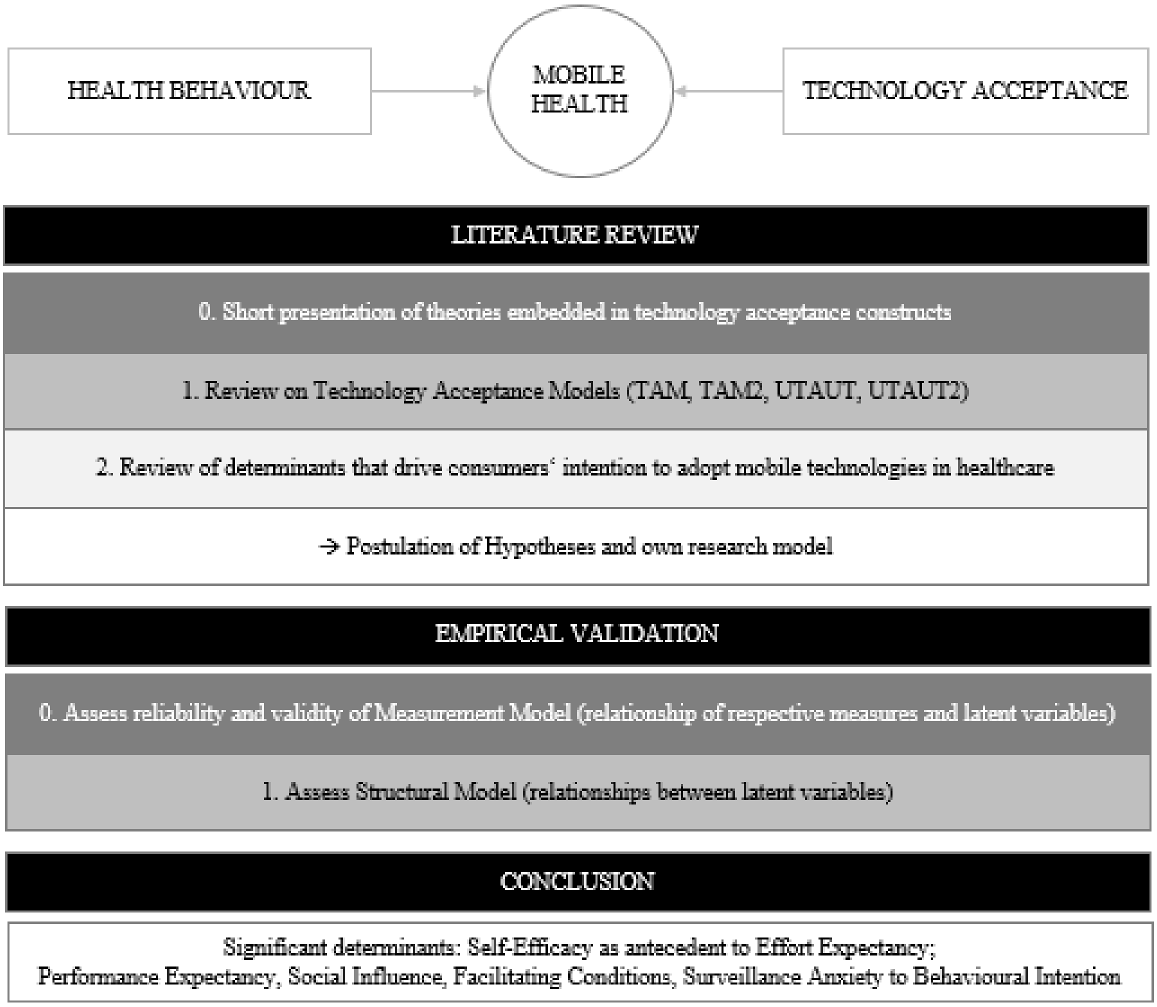
As a result, there is the need to examine a comprehensive framework on factors determining adoption of mobile technologies from the perspective of consumers, irrespective of age, health status and mobile health (hereafter: m-health) application used. Appertaining to this research gap, the perspective of impediments preventing adoption must be included. The research setting has been chosen to be Germany, to contribute to the limited European research of factors determining m-health adoption. Additionally, the set focus on one culture will prevent cultural diversities to distort findings and make the results specifically reliable for the German market. Due to its higher predictability, the basis of this research is the UTAUT model. It is extended by three constructs that account for the risk perspective. As a consequence, the postulated research model is then verified through the application of Partial Least Squares Structural Equation Modelling, as the objective of this thesis is to derive recommendations for developers, practitioners and marketers regarding factors that determine consumers' attitude towards m-health technologies. Only when patient's concerns towards the usage of such technologies are understood and factors promoting or preventing adoption have been identified, these applications can prove to be successful (Becker, 2016). Consequently, the overall research question can be formulated as:

"Which factors determine German consumers to have the behavioural intention to adopt m-health technologies?"

1.3 Structure of the Thesis

The following outline underlies the development of an answer to the research question: Chapter two will present understandings of the m-health concept, since it is not a precisely defined term. Further, facts from the healthcare industry will highlight the practical relevance of m-health. Chapter three first very quickly introduces the most prevalent behavioural change theories, as they often contribute to technology acceptance models, which are subsequently described. After a general presentation of these models, a discussion of constructs used in the context of m-health technologies from a consumer's perspective concludes. Based on the findings, hypotheses on factors influencing the Behavioural Intention to adopt a m-health technology (the study's goal) will be formulated. Next, chapter four will present the research methodology, hence the procedures for sample selection and data collection, as well as the research design applied. Chapter five starts with several validity and reliability tests of the proposed model, which are followed by the determination of the model's predictive power. A discussion on these findings follows and closes the chapter. Chapter six proposes theoretical and practical implications of the results and presents limitations of the current work as well as suggestions for future research on m-health technologies. Eventually, chapter seven concludes.

Figure 1: Illustration of the Research Outline



2. Significance of m-health

Since m-health is an emerging field within the healthcare industry, and the term has dispersed without any fixed underlying definition, there is the need to describe what is understood as 'm-health' within this work. Subsequently, m-health's impact on the German healthcare industry is illustrated.

2.1 The concept of m-health

E-Health, as the umbrella term, emerged around the turn of the millennial and basically encompasses everything that virtually connects computers and medicine (Eysenbach, 2001), thus healthcare services that are supported by electronic means. Schweitzer and Synowiec (2012) understand e-health as "the use of information and communication technologies for health" (p.73), therewith accounting for wireless signals and telecommunication. Embedding the relevance of e-health, Eysenbach (2001) describes it as a "state-of-mind" that does not only relate to technical advancements made at the intersection of public health, business and medical informatics but rather as an attitude of improving healthcare access, globally and locally. As can be concluded from this notion, the impact of m-health will go even beyond, as mobile phone possession has reached 60% in Germany according to the statitistics portal 'Statista'. Shareef et al. (2014) go as far as to say that with mobile health "the transformational healthcare service system is restructured and redesigned technologically, organisationally, and socially" (p.188), enabling people to seek medical advice from any remote place at any time through a mobile device. The understanding of Kumar et al. (2013) adds to this perspective the daily utilization of wireless devices and sensors, thus mobile equipment, to measure changes in the health status.

Concerning the functionality of m-health technologies, Dwivedi et al., (2016) describe it the following way: A radio-frequency identification (RFID) capable device, measures changes in the patient's health condition through a sensor that is externally worn or implanted in the user's body. The measurements are simultaneously submitted to a receptive mobile device, such as a smartphone. There, the recorded information is stored, so that it could allow for trend analyses over longer periods. Further, the information obtained can trigger alarms if a certain boundary value has been crossed (if e.g. the heart rate transgressed a certain threshold), give recommendations for counter-measures to the user and eventually, in cases of such an established connection, immediately transmit all recorded information to a physician, who is remotely located and analyses the data.

However, m-health technologies (or, as also quite often found in literature, ‘mobile health services’) do not exclusively focus on medical treatments, but also serve the idea of promoting fitness and wellness while being strongly user oriented (Demiris, 2012). The purpose is to enable and facilitate continuous health monitoring, the prevention and reduction of health problems, facilitation and support of patient’s self-management, enhancement of their understanding, and, ultimately, the encouragement of better health behaviour (Kumar, et al., 2013).

Regarding the effectiveness of m-health, no numerical evidence is so-far available. Yet, it is generally assumed that m-health technologies improve health management and outcome as well as help saving costs (Kumar, et al., 2013). Moreover, these applications support users attain their health goals while assisting on the journey of pursuing a healthier lifestyle (e.g. Andrews, et al., 2013). As proof of m-health’s potential, the yearlong study conducted by Franklin, et al. (2006) on 92 diabetes patients can be put forward. It showed that participants, who received daily text messages relating to the management of the illness, scored higher on self-efficacy and self-reported adherence. The correspondence was perceived as a strong means of support and 90% of the participants had wished to continue receiving messages after the study period was over. Similar observations were made by Andrews, et al. (2013) who studied the effects of SMS-assisted smoking cessation interventions.

2.2 Practical Relevance of m-health

The potential of digitalization and especially big data in the healthcare industry is tremendous: Communication paths will take new forms, information will be exchanged much faster and more precisely, medical supply and treatments will be more efficent while demand for health care services should decrease, therewith saving costs (McKinsey, 2016). Health start-ups spring up like mushrooms; according to the Digital-Health-Investment-Fonds Rock Health more than 4 Billion USD were invested in the United States in 2014, therewith accounsting for 9% of all venture funding (Gandhi & Wang, 2015). Resisting to change, the German healthcare industry is prone to disruptions by new market entrants and foreign investment, as industry experts worry about the trend of Asian enterprises acquiring German biotechs, withdrawing knowledge

(Ärzteblatt, 2016). Further, more and more technology companies start to offer m-health solutions, asking the smartphone user to bear the costs – and many do.

In line with this, it is foreseen by many actors of the healthcare industry that business models will change towards more customized contracts, where patients will benefit from individualized payment plans. Fees and premiums that have to be paid to insurers and providers will depend on the patient's effort to maintain or achieve a good health condition, whose endevours will thus be respectively rewarded (Cisco, 2016).

The need for a change in the healthcare system traces back to two main causes: First, the industry has to adapt to an increasing number of patients aging and suffering from chronic diseases, while availability of clinicians is limited (Laxman, et al., 2015) and costs need to be reduced. Second, customers' demands are becoming more specific and sophisticated (McKinsey, 2016).

To illustrate the magnitude of the first factor, the German Federal Office of Statistics reported that 4,213 Euros were spent on healthcare per inhabitant in 2015; in total corresponding to 11.3% of the German Gross Domestic Product (GDP). In comparison to the previous year, health costs increased by 4,5% in 2015, making it the fourth year in a row of stronger increase in health expenditures than GDP. The need for a less cost-intense and more efficient health care system is evident; and research done by McKinsey in 2016 found that a switch towards digital channels could save between 6.5% to 10.8% of total healthcare expenditures. Further, most illnesses that cause death, such as diabetes, cardiovascular diseases and cancer, result from a certain lifestyle (Deeks, et al., 2009). To fight against these results of obesity, smoking, too little physical activity, and others, education and more preventive methods are needed – and can easily be provided through online offerings. Even though many people have the intention to pursue a healthy lifestyle and consider it a priority, most of them state that they currently fail to do so (Deeks, et al., 2009)

Referring to the second point of more specific customer demands, smartphone users have been spoiled by big advancements due to digitalization occurring in other domains. Nowadays, consumers are used to get access to online shops, place food orders and schedule the deliveries according to their schedules. Technological advancements let people become more tech-savvy, therewith having also high expectations in the healthcare area: Patients look for highly personalized services round the clock and do believe that the Internet enables them to make better choices regarding their health (Kassirer, 2000). Additionally, they expect the services not only to be on-hand available whenever they need them, but to also provide qualitative and efficient medical advice at a low price (Dwivedi, et al., 2016).

The Federal Ministry of Health passed an e-health resolution in December 2015, which serves as an indicator that the German healthcare system will move towards a more digital era. The statute gives a broad timetable concerning the introduction of a digital infrastructure among players, to ensure highest security standards and pave the way for Telemedicine, Consumer Health Informatics, the Electronic Health Card and the possible integration of Smartphone Apps as another tool for communication in the healthcare sector (Bundesministerium für Gesundheit, 2017). Consequently, users' interaction with these technological offerings needs to be investigated.

3. Literature Review

In the beginning and very shortly, theories that look at behavioural change are described, as often some of the constructs were adapted and adopted to constructs of technology acceptance models, as e.g. within the UTAUT model (Venkatesh, et al., 2003). Subsequent to a more extensive but still general presentation of the prevalent various technology acceptance models, I discuss research models that have been postulated within the m-health context. As a consequence of the literature analysed, I develop my own hypotheses and model.

3.1 Behavioural Change Theories

Several theories exist that explain behavioural change, thus the decision to e.g. alter one's behaviour towards another one. Nutbeam (1998) defined health behaviour as "any activity undertaken by an individual, regardless of actual or perceived health status, for the purpose of promoting, protecting or maintaining health, whether or not such behaviour is objectively effective towards that end" (p. 355). Thus, behavioural change theories relate to m-health technologies in the sense that adoption is an undertaking to maintain or improve a health status. Reviews on Health Behaviour Theories (e.g. Munro, et al., 2007) discuss the Health Belief Model (HBM), Social Cognitive Theory (SCT), Theory of Reasoned Action (TRA), Theory of Planned Behaviour (TPB) and Protection Motivation Theory (PMT). These theories share the common perception that (health related) behaviour is the result of an interplay of attitudes, assessments of future happenings and cognitive variables triggering behavioural change (Munro, et al., 2007). Therewith, they have been quite often included to some extent in the constructs determining behavioural intention to adopt a technology. From these behavioural theories, did especially TRA, TPB and SCT contribute to the formulation of the UTAUT model (Venkatesh, et al., 2003). Therefore, the following presents very quickly the constructs and ideas of the five most relevant behavioural change theories.

The **Health Belief Model** (HBM) (see Appendix 1) was originally developed by several social psychologists of the U.S. Public Health Services in the 1950s. The model suggests that, under the lack of symptoms, a subject will undertake preventive measures only if it is ready to take action. In turn, this is determined by the person's susceptibility to the potential (threatening) condition and the perceived seriousness of a given health problem. If susceptibility is accepted, this will impact a person's 'perceived benefits of taking an action' as well as the 'perceived barriers to take action'. Ultimately, 'cues to action' will determine a person's health behaviour (Rosenstock, 1974).

Social Cognitive Theory, introduced as the Social Learning Theory by Bandura in the 1960s and subject to several amendments and changes, is grounded on the belief that an individual's behaviour is influenced by its social environment, thus, behaviour is an outcome of the interaction with other people, their behaviour and the environment (LaMorte, 2016).

Protection Motivation Theory (PMT), by Rogers (1975) (Appendix 2) includes the factors of perceived vulnerability, perceived severity, perceived response efficacy and perceived self-efficacy. The theory assumes that behavioural change is the result of appealing to an individual's fears, and by weighing costs and benefits of the status quo compared to the recommended behaviour; therewith triggering behavioural change (Munro, et al., 2007). Sun, et al., (2013) studied technology acceptance in the m-health context by condensing TAM, UTAUT and PMT together with TPB.

The Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975) (Appendix 3) views behaviour as the outcome of Behavioural Intention, which is determined by Attitude and Subjective Norm. Attitude was defined as "an individual's positive or negative feelings (evaluative affect) about performing the target behavior" (p.216) and Subjective Norm as "the person's perception that most people who are important to him think he should or should not perform the behaviour in question" (p.302). TRA is an especially well-researched intention mode1 that has proven successful in predicting and explaining behaviour across a wide variety of domains. Since TRA is very general, "designed to explain virtually any human behavior" (Ajzen and Fishbein 1980, p. 4), it is thus appropriate for studying the determinants of computer usage behaviour as a special case. Therefore, the concept has been integrated in many researches concerning technology acceptance, and contributed to the postulation of UTAUT.

The **Theory of Planned Behaviour** (TPB), (Appendix 4) postulated by Ajzen (1991) extends TRA and assumes that intention predicts target behaviour. Intention is influenced by three constructs, namely Attitude, Subjective Norm and the newly added construct of 'Perceived Behavioural Control'. The latter construct refers to "people's perception of the ease or difficulty of performing the behavior of interest" (p.183) and varies depending on situation in which the person makes the evaluation.

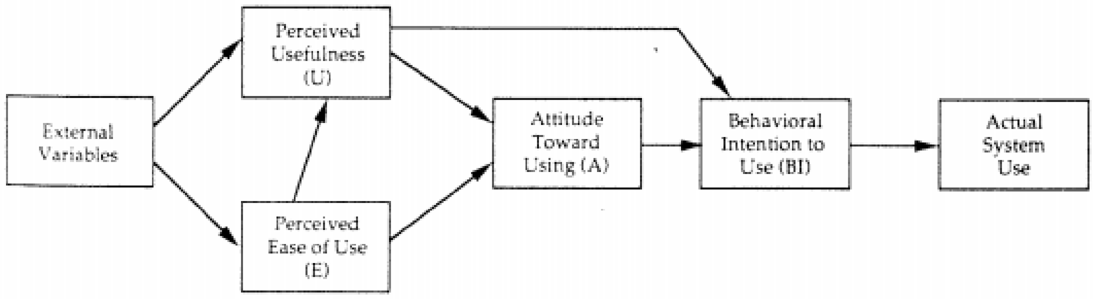
3.2 Technology Acceptance Models

As Rao & Troshani (2007) note, several different theoretical models exist that describe innovation adoption, each with a slightly different focus depending on the target adopter as well as the setting. These various models all aim to find explanations on what drives consumer's intention to adopt an innovation or technology. Out of this reason, Venkatesh et al. (2003) merged several prevalent theories together to form the Unified Theory of Acceptance and Use of Technology. The aggregated theories that contributed to the unified model are: Theory of Reasoned Action (TRA), the Technology Acceptance Model (TAM), the Motivational Model (MM), the Theory of Planned Behaviour (TPB), a combined model of TAM and TPB (C-TAM-TPB), Innovation Diffusion Theory (IDT), Social Cognitive Theory (SCT) and Model of PC Utilization (MPCU). As consequently the UTAUT model is superior in predicting technology acceptance (Venkatesh et al., 2003), this model will be ultimately adopted for the research of this study. However, since many researchers still adopt the Technology Acceptance Model (which is part of the UTAUT) and extend it by adding constructs from e.g. TPB (e.g. Sun et al., 2013), this model also seems to be relevant in technology adoption in healthcare. Thus, since both were frequently utilized in predicting mobile health adoption, the conceptualisations of these two models will be subsequently described more extensively, before analysing models that have been applied in consumer's adoption intention of m-health technologies.

3.2.1 Conceptualization of the TAM

The TAM (Figure 2) postulated by Davis et. al in 1989, has been widely used to explain acceptance of information technology in the healthcare context due to its high reliability, as it most often explains between 30% to 40% of variance in usage intentions and behaviours, as Holden & Karsh (2010) condensed in their review of 20 studies of clinical personal using health IT. Further, TAM has been well explaining technology acceptance in a voluntary as well as mandatory setting (Venkatesh & Davis, 2000), therewith being suitable for m-health studies.

Figure 2: Technology Acceptance Model, Davis et al. (1989)

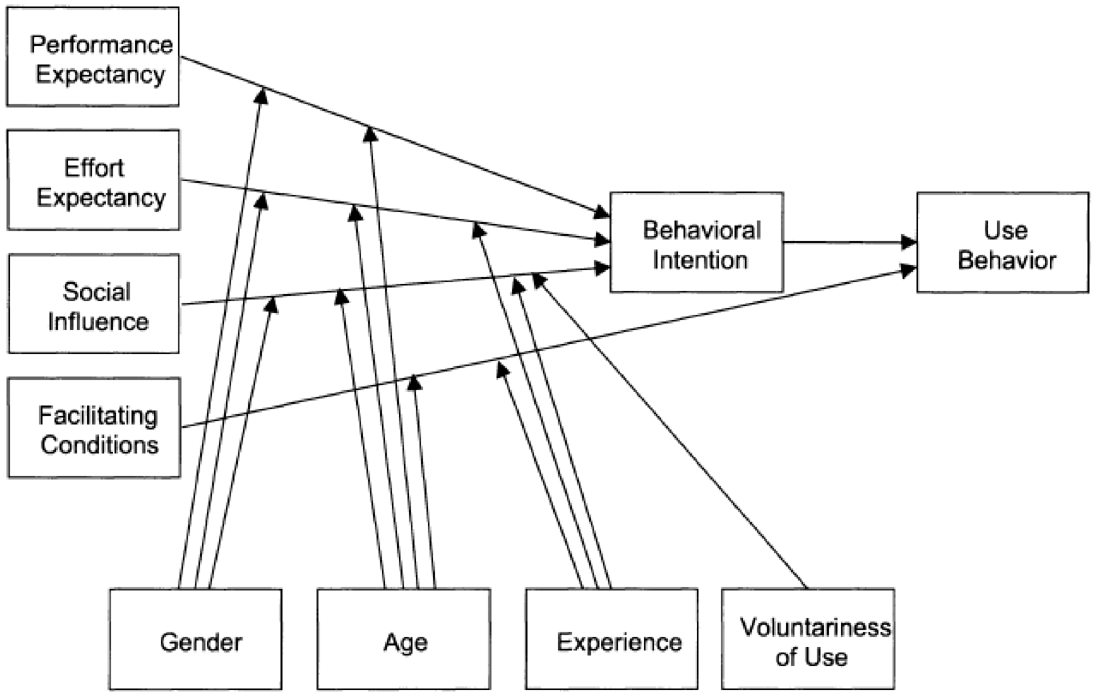


Based on the Theory of Reasoned Action, Davis and Davis et al. (both 1989) postulated that Behavioural Intention to Use was directly influenced by Perceived Usefulness (PU) and Attitude towards Using, as well as indirectly through Perceived Ease of Use (PEOU). Whereas Attitude was equally impacted by PU and PEOU, the latter one was said to also have an influence on PU. As the initial setting of the studies was within work context, PU had been defined as "the degree to which a person believes that using a particular system would enhance his or her job performance" (pp.320) and PEOU as "the degree to which a person believes that using a particular system would be free of effort" (pp.320). Results from their regression analysis had indicated PEOU to be a precursor for usage and thus not an equal determinant to usage, as easiness to use enhances the perceived usefulness of a system. Further, both determinants are said to be influenced by external variables, such as system characteristics or training, to name a few. Later, Venkatesh & Davis (2000) adapted TAM to TAM2 (Appendix 5), by including several antecedents to PU and removing the construct of attitude. Therefore, other constructs, namely from social influence processes (subjective norm, voluntariness and image) and from cognitive instrumental processes (job relevance, output quality, result demonstrability, and perceived ease of use) were added. In fact, it was found that Subjective Norm has a very strong impact on usage intention (Venkatesh & Davis, 2000).

3.2.2 Conceptualization of the UTAUT

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a widely-known tool to measure behavioural intention, due to its precise predictability of around 70% of variance in behavioural intention and around 50% of variance in technology use (Venkatesh, et al., 2003). Venkatesh, et al. (2003) postulated the theory to condense all prior existing theories thematising technology acceptance. Therefore, they reviewed eight theories of in total 32 constructs that utilize intention and/or usage as a dependent variable in the context of individual technology adoption or on organizational level. In conclusion of their empirical work, the determinants of Performance Expectancy, Effort Expectancy and Social Influence were found to be direct antecedents of Behavioural Intention, whereas in turn Behavioural Intention and Facilitating Conditions were identified to determine Usage (see Figure 3). All variables except Behavioural Intention were postulated to be moderated by age, gender, experience and voluntariness to use, as – similar to TAM – UTAUT was initially developed and empirically validated for technology usage in an organizational context (Venkatesh, et al., 2003).

Figure 3: UTAUT Model, Venkatesh et al. (2003)



Venkatesh et al. (2003) defined *Performance Expectancy* as “the degree to which an individual believes that using the system will help him or her to attain gains in job performance” (p. 447). In view of TAM, it is relevant to mention that this determinant corresponds to the concept of Perceived Usefulness from the TAM/TAM2 and C-TAM-TPB and extrinsic motivation from MM. PE has been empirically found to be the strongest predictor for intention in several researches (Venkatesh, et al., 2003; Lim, et al., 2011; Hu, et al., 1999). *Effort Expectancy*, defined as “the degree of ease associated with the use of the system” (Venkatesh, et al., 2003, p.450) corresponds, amongst other of the reviewed concepts, to Perceived Ease of Use in the context of TAM/TAM2. The third determinant with a direct influence on BI is *Social Influence*, which Venkatesh et al. (2003) defined as “the degree to which an individual perceives that important others believe he or she should use the new system.” (p.451). It is based on the construct of Subjective Norm which was used in several of the eight combined theories. While

Venkatesh et al. (2003) argue that the influence of others has a stronger effect on BI in mandatory settings, research has shown that it is a strong predictor for BI also in voluntary settings (e.g. Andrews, et al., 2013; Gao, et al., 2015). Lastly, *Facilitating Conditions* are defined as "the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system" (Venkatesh, et al., 2003, p. 453). Consistent with their initial hypothesis, that FC do not to have a significant impact on BI, but a direct effect on usage, empirical evidence was found. The concept resembles the construct of Perceived Behavioural Control from Ajzen's (1991) postulated Theory of Planned Behaviour. *Attitude*, a construct that relates to feelings associated with technology usage, was defined as "an individual's overall affective reaction to using a system" (Venkatesh et. al, 2003, p.455). While the researchers initially obtained contradictory results on the importance of attitude on BI, they eventually identified that attitude would become significant only if the constructs of EE and PE as predictors of BI were omitted.

While Venkatesh & Davis (2000) had modelled Self-Efficacy and Attitude to be mediated by PEOU, they hypothesized Self-Efficacy and Anxiety not to have a significant influence on BI in 2003. This is somewhat surprising, as Self-Efficacy and Anxiety were found to be significant important factors in Social Cognitive Theory (e.g. Compeau & Higgins, 1995) but however do not form part of the UTAUT. Venkatesh & Davis (2000) stated that Self-Efficacy and Anxiety are theoretically and empirically different from Perceveied Ease of Use (TAM)/Effort Expectancy (UTAUT) and are mediated by PEOU. Moreover, Behavioural Intention has been shown to have a positive influence on usage (Venkatesh, et al., 2003).

To study technology acceptance specifically in the consumer context, Venkatesh et al. postulated UTAUT2 in 2012 (Appendix 6), where the constructs of Hedonic Motivation, Price Value and Habit were added to the original UTAUT.

3.2.3 Discussion of models and applications in consumer's m-health adoption

As both models, TAM and UTAUT had been initially developed to study acceptance in an organizational context, most researchers made extensions to the original model to adapt for the consumer-centric factor as well as the specific setting which is to be studied. As with technology the whole healthcare system will progressively change from an institution-centric towards a user-centric approach (Demiris, 2012) several researchers have studied m-health acceptance. However, only the few studies that have been reviewed and aggregated below, have specifically targeted the identification of determinants that drive consumer's (and not physician's) intention to adopt mobile technologies.

In the healthcare context, the TAM has been frequently used, to e.g. study consumer's acceptance of technologies in Taiwan, Hong Kong, Australia and the US (Holden & Karsh, 2010). Researchers often focused on the treatment of a specific illness, as e.g. Becker (2016) applied TAM to study young consumer's adoption intention of mobile mental health applications and added constructs of Task-Technology Fit and Trust. Andrews et al. (2013) studied the success of SMS-based smoking cessation interventions. Cho, et al. (2014) analysed adoption of smartphone health apps based on TAM2, as it includes Social Influence. Jen & Hung (2010) studied m-health technology adoption by families as a tool to care for their elderlies based on a combination of TPB and TAM. Dwivedi, et al. (2016) reviewed theories on marketing and channel preferences, and hence extended the model of UTAUT2 by constructs of. Waiting Time and Self-Concept. Gao, et al. (2015) analyse technology acceptance of health wearables from a combination of UTAUT2, PMT as well as privacy calculus theories. Several other researchers, have rearranged constructs from the theories presented in 3.1 and 3.2, and tested various constructs. Regarding barriers of adoption, reseachers have identified multifold obstacles. Laxman, et al. (2015) study consumer health informatics and find privacy and security concerns to be an obstacle, despite consumer's general willingness to adopt consumer health informatics. Akter (2013) supports this view and adds that uncertainties regarding the quality of mobile health services exist as they lack reliability. Bansal, et al. (2010) find reservations concerning the privacy reagrding personal health information. Peng, et al. (2016) pursued a qualitative study on user's perception of health apps and found the lack of need to be one of the reasons preventing adoption. Becker (2016) finds, that young adults in Germany question the effectiveness of mobile applications. The findings on the most frequent constructs in the m-health context analysing consumer's intention are discussed in the following. Constructs that have been found to be conceptually similar, as e.g. Performance Expectancy (UTAUT) and Perceived Usefulness (TAM) are aggregated. Attitude as a construct predicting BI has been examined by only a few researchers (e.g. Jen & Hung, 2010; Deng, et al., 2014; Shareef, et al., 2014), most likely due to the findings by Venkatesh et al. (2003) that it is not relevant if PE and EE are included as constructs that predict BI, and will thus not be discussed.

Perceived Usefulness/Performance Expectancy

Regarding PE, Yuan et al. (2015) find positive influence on BI in the context of health apps and Eysenbach (2016) obtains similar results. In relation to mobile health services, several researches find a positive influence of PE on BI, e.g. Lee & Han, 2015; Jen & Hung, 2010; Dwivedi et al., 2016; Andrews et al., 2013; Shareef et al., 2014. Several researchers have hypothesized a mediating effect of PU on the relationship of PEOU and BI (e.g. Jen & Hung, 2010; Shareef, et al., 2014; Eunjoo & Park, 2015). Moreover, Cho, et al. (2014) identify Health Consciousness and Subjective Norm to be predecessors of PU.

Perceived Ease Of Use/Effort Expectancy

Cho, et al. (2014) and Andrews, et al. (2013) did not find evidence for a significant effect of Perceived Ease of Use on Behavioural Intention. Whetstone & Goldsmith (2009) excluded the construct from their research model, arguing that testing a newly introduced Personal Health Record would not allow for reasonably measuring PEOU because of lacking experience. Contrasting, Jen & Hung, 2010; Eysenbach, 2016; Sun, et al., 2013; Dwivedi, et al., 2016; Shareef, et al., 2014, find a positive relationship of PEOU on BI.

Facilitating Conditions

The impact of FC on BI was found to be non-significant by Yuan, et al. (2015). Dwivedi et al. (2016) argue that a flawless interaction of host and service provider, as well as the absence of concerns for privacy and security issues will have a positive impact on BI and find corresponding empirical evidence. Gao, et al. (2015) substitute the concept of Facilitating Conditions by utilizing Self-Efficacy, as they argue that users could not adopt healthcare wearables if they had not the knowledge and ability to operate these tools. Through the concept of Self-Efficacy, they find a very strong relationship on BI.

Self-Efficacy

Self-Efficacy is defined as "judgments of how well one can execute courses of action required to deal with prospective situations" (Bandura, 1982, p.122). Becker (2016) uses Self-Efficacy as a direct determinant of Behavioural Intention and finds a significant relationship. Supporting this result, Sun, et al. (2013) find Self-Efficacy to be the third most important factor influencing BI. However, when Eunjoo & Park (2015) use Self-Efficacy as a predecessor of PEOU and PU, they do not obtain a significant relationship. Lim, et al. (2011) argue that Self-Efficacy is influenced by gender, as to the fact then men usually tend to have higher levels of Self-Efficacy than women. However, they did not test for any moderating effects as they included Self-Efficacy as a direct determinant of BI while studying female subjects, for which they found a positive relationship.

Hedonic Motivation

Hedonic Motivation is a construct from UTAUT2 (Venkatesh, et al., 2012) that describes the intrinsic motivation, thus, the enjoyment of using a m-health technology. It was not found to be significant by Eysenbach (2016). This finding contradicts results of research pursued by Yuan et al. in 2015 as well as by Gao et al. (2015), who both find a significant relationship. Dwivedi, et al. (2016) who empirically validate their model in three different countries, do find a non-significant relationship for Canada and USA, but a significant one for Bangladesh. Similarly, Andrews et al. (2013) do not find a significant relationship between Hedonic Motivation and BI for the Western world, i.e. France, but for Mexico and Australia.

Social Influence/Subjective Norm

Cho, et al. (2014) found, that subjective norm and health information orientation had positive and significant impacts on PU. Subjective Norm was found to be supported in influencing behavioural intention in several studies within the m-health context (e.g. Andrews, et al., 2013 for Australia and Mexico; Sun et al., 2013; Gao, et al., 2015). Contradicting these findings, Jen & Hung (2010) obtain a non-significant influence of SN on BI but argue, that due to the upper social class the Chinese respondents belonged to, they do not take referents' opinions much into account. Similar results are obtained by Deng, et al. (2014), who also study Chinese consumers. Eysenbach (2016) as well as Yuan et al. (2015) also do not find any significant effect on BI and Andrews et al. (2013) do not find it for France.

Price Value

Price Value, a determinant developed to measure the trade-off between the perceived benefits and the costs incurred for adopting a technology, is meant to represent consumers' cognitive reflections (Venkatesh, et al., 2012). Eysenbach (2016) does not find price value to be significant to predict BI. However, results obtained by Dwivedi et al. (2016) and Yuan et al. (2015) do not correspond, as they find a positive impact of Price Value on BI. Correspondingly, the hypothesis by Lee & Han (2015) that monetary value has a positive impact on BI is supported. Gao, et al. (2015) summarize price value and perceived quality of a product as the construct of 'Functional Congruence'. The argumentation is that price is not a standalone factor for adopting a healthcare wearable, as e.g. ergonomic design might impact the consumer's decision for paying a certain price. However, they find this construct to be less relevant.

Privacy

Angst & Agarwal (2009) find concerns for privacy information to be an important influence on individual's attitude to use Electronic Health Records. Becker (2016) identifies a prevalent concern of unwanted disclosures of personal information throughout his study on young consumer's acceptance of mobile mental health treatment applications. Shareef, et al. (2014) as well as Dwivedi, et al. (2016) note the issues of security, privacy and trust to be one of the main concerns preventing the adoption of Internet-based products/services. Gao, et al. (2015) and Whetstone & Goldsmith (2009) find perceived privacy risk to be one of the strongest factors predicting BI. Congruent, Shareef, et al. (2014) find Perceived Privacy and Security Risk to have a significant impact on BI. Becker (2016) utilizes the construct of Trust, as he argues that trust provides more security of personal data and finds a significant impact on BI.

Health Condition

Interestingly, Deng, et al. (2014) study the effect of Perceived Physical Condition on BI and do not find any significant impact. In line with this, Lee & Han (2015) hypothesize that an individual with illness' experiences is more likely to adopt m-health technologies is rejected. Eysenbach (2016) adds the construct of self-perception from the Health Belief Model, which describes that an individual's perception of his/her health determines whether he/she takes a certain health-related action. The researchers find a significant impact. Sun, et al. (2013) add Threat Appraisals taken from the Protection Motivation Theory, which are represented by the constructs of Perceived Vulnerability to and Perceived Severity of suffering from a certain health condition. For the latter construct, they do not find a significant influence on BI. Gao, et al. (2015) follow a similar approach as Sun, et al., but find significant relationships on both constructs and BI.

Technology Anxiety

Technology Anxiety is a construct from Social Cognitive Theory and describes the discomfort people experience when (thinking of) using a technology (Deng, et al., 2014). Lim, et al. (2011) find Technology Anxiety not to have a significant negative impact on BI, therewith limiting its presumed influence on BI. Deng, et al. (2014) find the relationship between Technology

Anxiety and BI to vary according to age; while the relationship is significant for older consumers, it is found to be irrelevant for the middle-aged group.

Habit

Habit, a construct newly added to UTAUT and thus part of the UTAUT2 (Venkatesh, et al., 2012), describes to perform certain behaviours due to a learning effect and is formulated to be a direct predecessor of usage as well as BI. Dwivedi, et al. (2016) discuss the applicability of Habit but since they do not measure prior behaviour, the construct is not included in their research. Yuan, et al. (2015) include Habit as a construct and find it is a significant predecessor of BI for continued usage of health apps.

Other constructs

Following, other constructs, that were found to be interesting and yielding surprising results are shortly discussed. Health consciousness, a construct incorporated by Cho, et al. (2014), describing the awareness and care one dedicates to his/her health condition, has been found to have a negative impact on the intention to use health apps. To explain this puzzling result, the researchers hypothesize that health-conscious users might have established routine health behaviours like physical exercise and eating habits, so that additional activities like the usage of health apps would not be perceived as additional value.

Dwivedi, et al. (2016) add the construct of Waiting Time as an indicator for user's service requirements, and predict it to have a positive influence on BI. Perceived Compatibility and Perceived Reliability are added by Shareef, et al. (2014) which are found to be not significant respectively significant.

Moderating Effects

Moderating Effects have been widely included in the research conducted related to UTAUT and UTAUT2 but also other studies with different constructs. Moderating variables are third variables that are believed to influence the relationship between two other variables, e.g. between the independent and the dependent variable (Hair, et al., 2014). Venkatesh, et al. (2012) postulated age, gender and experience to have moderating effects on Facilitating Conditions, Hedonic Motivation, Habit and Price Value. Jen & Hung (2010) find gender to be an important moderator, since males' intention to adopt m-health technologies is stronger than those of females. Eysenbach (2016) finds that age has a moderating effect on Habit. Further, he investigates a moderating effect of chronic disability, but does not find an effect. Yuan, et al.

(2015) include the moderating effects of UTAUT2, namely gender, age and experience in their model but do not find empirical evidence. Lee & Han (2015) include gender, age and income not as moderating effects but as constructs directly influencing adoption intention, but do not find significant effects. Gao, et al. (2015) predict product type to have a moderating effect on the determinants influencing BI and find empirical evidence. On the contrary, Whetstone & Goldsmith (2009) do not find support for predictive power of age or gender on BI. In fact, Or & Karsh (2009) state that age has not been found to render a consistent effect throughout prior research on Consumer Health Information Technologies and that gender did not have any impact in 84% of the studies that included the construct.

Behavioural Intention

Behavioural Intention was found to be significant by Dwivedi, et al. (2016) for predicting adoption behaviour. Lim, et al. (2011) do not find that BI predicts usage, as they find a gap between intention and usage. They try to explain this occurrence through limited time survey respondents spent on the application as well as an offering, that was not tailored to their needs. Other researchers only studied BI as the outcome variable and not actual usage.

3.3 Hypothesis Development

Under consideration of the findings from the general models as well as those from a user's perspective in the healthcare context, I will postulate hypotheses on relationships between exogenous and endogenous variables to examine consumer's behavioural intention to adopt a m-health technology.

As An, et al. (2007) note, it is important to adopt the underlying technological model to the specific context of the study's purpose and make adaptations to the specific setting. Dwivedi, et al. (2016) add, that an extended model needs to take e.g. cognitive and affective behavioural aspects of an individual into account. Thus, to conceptualize a model that is reliable in predicting *consumer's* intention of technology adoption from a general perspective, several factors that have been proven to be of interest based on the discussion of literature's findings in 3.2 are included in the research model of this work. Due to the higher validity of UTAUT ranging around 70% compared to TAM's reliability of around 30-40% validity in predicting Behavioural Intention (Venkatesh et al., 2003), the research model was developed based on the UTAUT. In an empirically validated study on acceptance of mobile health services, Sun, et al.

(2013) compare TAM, TPB and UTAUT among 204 Chinese and find evidence supporting the superior predictability of the unified model. Further, to complement the positive utility constructs with negative utility constructs as Featherman & Pavlou (2003) suggested, three constructs representing potential losses are added. In detail, those are Surveillance Anxiety, Physical Risk and Perceived Privacy and Security Risk. Finally, acceptance of technology refers to behavioural intention in line with the most often used notions (Holden & Karsh, 2010) and is thus the outcome variable.

Performance Expectancy

Performance Expectancy, a concept corresponding to PU from TAM/TAM2 model, has been found to be the strongest indicator for behavioural intention (e.g. Venkatesh, et al., 2003; Andrews, et al., 2013; Lim, et al., 2011). If the user believes that using a technology will help him attain a certain health condition, he is more likely to adopt the technology. In line with prior research advocating this positive relationship (e.g. Rogers, 1975; Dwivedi, et al. 2016; Venkatesh, et al., 2012), it is hypothesized that:

***H1**: Performance Expectancy has a positive influence on the behavioural intention to use m-health technologies.*

Effort Expectancy

Effort Expectancy (EE) roots back to the concept of Perceived Ease of Use in the TAM/TAM2 models. Since technology has pervaded almost every area of life, users will only adopt a technology if it is easily understandable and useable (Dwivedi, et al., 2016). Therefore, a user will adopt m-health technologies according to degree of ease with which he can use it. Therefore, it is formulated that:

***H2**: Effort Expectancy has a positive influence on the behavioural intention to use m-health technologies.*

Social Influence

Dwivedi, et al. (2016) argue that SI is relevant in the m-health technology context as the interaction with the m-health technology is likely to be observed by others in daily life, and that aspirational reference groups' influence will lead to adhesion of using the technology. Further, Venkatesh et al. (2000) argue that SI is important for adoption if a technology is at its early stage. Consequently, it is theorised that:

H3: *Social Influence has a positive influence on the behavioural intention to use m-health technologies.*

Facilitating Conditions

Facilitating Conditions, the degree to which individuals expect to obtain support in using a system from the organizational and/or technical environment (Venkatesh et al., 2003) have been shown to impact BI. Dwivedi et al. (2016) find that factors like an effortless interaction with the m-health provider as well as his perceived reliability to positively influence BI. Consequently, I formulate the hypothesis that:

H4: *Facilitating Conditions have a positive influence on the behavioural intention to use m-health technologies.*

Self-Efficacy

Bandura (1982) found that higher levels of Self-Efficacy cause higher levels of performance accomplishments. Venkatesh & Davis (1996) found empirical evidence for Self-Efficacy as an antecedent for Perceived Ease of Use and later (2000) modelled Self-Efficacy as an indirect determinant to BI, mediated by Perceived Ease of Use. Therefore, it is hypothesized that:

H5: *Self-Efficacy has a positive influence on Effort Expectancy.*

Physical Risk

The construct of Physical Risk has been added according to Featherman & Pavlou's (2003) approach to complement technology adoption research by including constructs for potential losses that might result from adopting a technology. Since m-health technologies are expected to substitute personal contact with a physician (Demiris, 2012), users might be concerned about not detecting signs as a doctor would. Hence, it is theorised that:

H6: *Perceived Physical Risk has a negative influence on the behavioural intention to use m-health technologies.*

Surveillance Anxiety

Kummer, et al. (2017) study technology induced anxiety and its effects on adoption of sensor-based technology. He notes that particularly German users most often worry about the permanency of surveillance, have concerns regarding the increased transparency and insecurities on what and when the system monitors, as mobile devices operate independently and invisibly. Consequently, users are concerned with privacy violation and being exposed. To validate the researcher's finding that Surveillance Anxiety does not have a significant negative impact on BI, I still include the hypothesis that:

***H7**: Surveillance Anxiety has a negative influence on the behavioural intention to use m-health technologies.*

Privacy and Security Risk

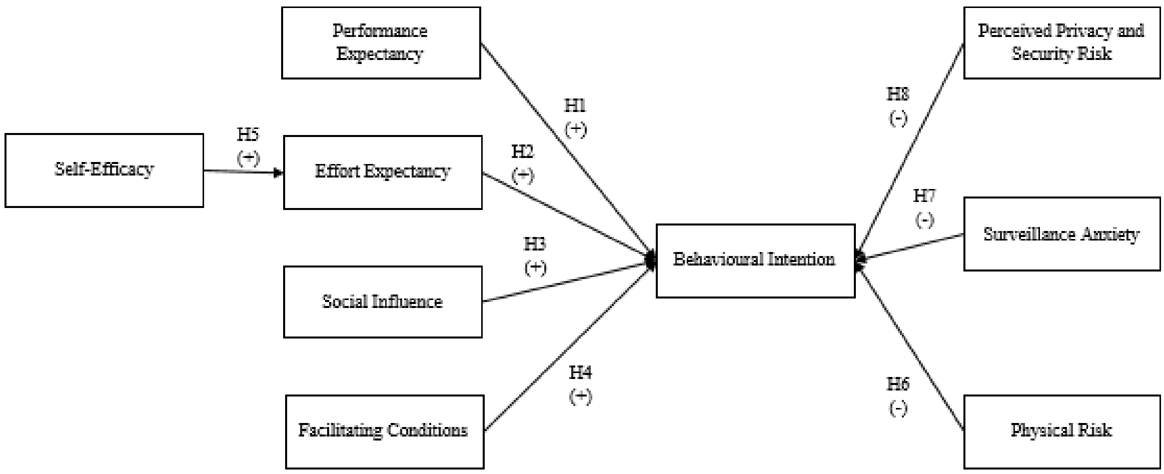
Bansal, et al. (2010) define privacy concerns as the fear of not being in control of personal information, of not being sure that information is exchanged securely and about the reliability of the receptionist on treating the obtained information confidentially. Laxman, et al. (2015) find that privacy and security risks are, besides costs, one of the main concerns preventing usage of consumer health informatics applications for health self-management. Shareef, et al. (2014) argue that healthcare service over mobile technologies are vulnerable to security threats as well as the disclosure of private information. As the adoption of m-health technologies requires the user to continuously provide sensitive data, it is hypothesized that:

***H8**: Perceived Privacy and Security Risk have a negative influence on the behavioural intention to use m-health technologies*.

Behavioural Intention

Taylor & Todd (1995) reviewed several models for IT Usage and found BI to be the most important determinant for predicting actual behaviour regarding IT usage. In line with this, Sheppard (1998) and Ajzen (1991) examined intention as the feelings an individual has about performing a target behaviour to be a predictor of behaviour. That view is supported by findings of Venkatesh et al. in 2003 and 2012, as they state that most studies deploy intention and/or usage as the key dependent variables. Chau & Hu (2002) argue that intention is suitable and appropriate as a measure when a technology is at its early stage and thus usage is not yet widely spread.

Figure 4: Research Model



The path diagram (Figure 4) illustrates the hypothesized model. To subsume, PE, EE, SI and FC are expected to have a positive influence on BI. The construct of EE is expected to be mediated by Self-Efficacy through a positive relationship. The constructs of PR, SA and PS are hypothesized to have a negative impact on BI. The latent constructs of PE, SI, FC, SE, PR, SA and PS are exogenous variables, meaning that they are not caused by another variable (no structural relationship is pointing at them). BI is an endogenous variable, as it is caused by the influence of the exogenous variables through the structural relationships. The variable of EE is a special case as it is both, a cause and effect variable – it is influenced by SE, but causes BI.

In line with research results from Venkatesh, et al. (2003), attitude is neglected in this research model, as PE and EE are hypothesized to be direct determinants of BI, therewith making the construct of Attitude obsolete. Further, moderating variables are not included in the research model, since experience cannot be measured and age and gender have not been consistently proven to have moderating effects and been neglected in more recent studies (e.g. Dwivedi, et al.,2016). In line with the majority of the studies reviewed, BI is the dependent variable studied (e.g. Andrews, et al., 2013; Sun et al., 2013; Eysenbach, 2016; Whetstone & Goldsmith, 2009). To include the argument of potential losses and follow the argumentation of Stone & Grønhaug (1993) to measure Perceived Risk by several dimensions, the constructs of Physical Risk and Perceived Privacy and Security Risk were added, besides Surveillance Anxiety from Kummer et al. (2017).

4. Research Methodology

The goal of this study is to determine factors, that influence a consumer's decision to adopt a m-health technology in Germany. Based on the literature review of technology acceptance in the m-health context, hypotheses were postulated in 3.3. Consequently, a research model with the seven constructs of PE, EE, SI, FC, PR, SA and PS directly influencing BI was developed. Self-Efficacy is expected to positively influence EE and thus its effect on BI will be mediated through EE. Since I want to validate whether the aforementioned constructs influence consumer's adoption intention, a quantitative approach was needed. It allows to test for the characteristics to determine the set of facts that drive consumers' adoption behaviour. A qualitative approach would have been more appropriate to inquire in-depth motivations and opinions of a smaller group of people to find factors that they find important when thinking of adopting a m-health technology. The research environment of this study is set in Germany, since it is very likely that digital health offerings will become more and more the standard in Germany – while it is also one of the countries most concerned with privacy and security issues (Hornung & Schnabel, 2009) and is therewith suitable for the development of a more conservative model.

4.1 Measurement

To measure consumer's adoption intention, a questionnaire was developed that consisted of three main parts (see Appendix 7). In total, 44 questions were asked, of which 4 were demographics, 6 asked for experiences with m-health technologies and 34 items were part of the Structural Equation Model (SEM). Preceding the questions, a short introduction briefly explained the concept of m-health technologies, insofar that the term itself, the way m-health technologies work and fields of application (e.g. wellness/fitness, medical surveillance of i.e. diabetes patients, exchange of patient health records) were explained. The motivation behind was to establish a common base for understanding the practicability of m-health technologies among all respondents as well as to educate unknowledgeable participants. Despite the fact that some researchers express the need for caution when presenting a concept to not influence respondents and create a bias (e.g. Sheng, et al., 2008) several researchers from the m-health domain have applied an introductory note that illustrated or defined the concept (e.g. Lee & Han, 2015; Dwivedi, et al., 2016; Whetstone & Goldsmith, 2009). I followed this approach for two reasons: First, respondents do not have the chance to ask for immediate clarifications, as it might be the case for e.g. face-to-face interviews. Second, m-health technologies are still at a quite early stage and thus – yet some people might already be using health wearables and health apps – might not be familiar that these applications go by the name of m-health technologies (since the whole concept is not very strictly defined, as seen above in 2.1).

Subsequently, the first part asked the respondent to provide information about his general personal characteristics, that is to say gender, age and possession of a smartphone/tablet and nationality. I put the questions for demographics in the first place to assure the respondent that no more than this personal information would be requested, due to the sensitivity of this topic and people's concern for anonymity.

The second part examined respondents' experiences with m-health technologies. It was neither a result of the literature review nor part of the Structural Equation Model but intended to gather insights on the status quo of m-health technologies in Germany: The first three questions asked for the usage frequency of m-health technologies within the three application areas of fitness/wellness, medical and administrative. The other three questions asked the respondent to assess the degree of familiarity of m-health technologies within his social environment as well as to evaluate m-health's efficacy in terms of health goal attainment and security (e.g. for cardiac/diabetic patients).

Part three included the measurement instruments of the SEM, which were based on scales adapted from prior literature. Performance Expectancy was measured through a four-item scale derived from Venkatesh, et al., (2012), Sun, et al., (2013) and Whetstone & Goldsmith (2009). Four items were used from Venkatesh, et al. (2012) and Dwivedi, et al. (2016) to measure Effort Expectancy. The three Self-Efficacy items were adapted from Sun, et al. (2013). The construct of Social Influence was based on three items deployed by Venkatesh, et al. (2012). The four questions for Facilitating Conditions were taken from Dwivedi, et al. (2016). The construct of Surveillance Anxiety was adapted from research done by Kummer, et al. (2017) and measured through four items. Measurement for Physical Risk followed three items from Stone & Grønhaug (1993). Perceived Privacy and Security Risk was adapted from Shareef, et al. (2014) and quantified through six items. Ultimately, the three measurement scales for Behavioural intention were adapted from Venkatesh, et al. (2012).

In line with several prior works (e.g. Dwivedi, et al., 2016; Gao, et al., 2015; Cho, et al., 2014; Lee & Han, 2015) all items were measured using five point Likert scales with the extremes ranging from 1 (strongly disagree) to 5 (strongly agree).

The finalized questionnaire was then translated into German and back-translated to English by a peer to check for proper translation and clear wording, similar to approaches of e.g. Kummer et al. (2017). Subsequently, a pilot test with ten respondents from different age groups was run to test for comprehension, perspicuity of language and duration to respond, to ensure clarity for participants of all ages. Small adaptations were made according to the suggestions.

4.2 Data Collection

Data Collection was attempted through a multimode approach, i.e. through an online survey as well as through the distribution of the respective hard copy to complement results. As commonly known, online surveys are an efficient, cost-saving and fast-response providing tool which can be accessed remotely from any geographic location (Ilieva, et al., 2002; Albaum, et al., 2010). Further, Ilieva, et al. (2002) condense several sources of evidence that web-based and email surveys provide more detailed and complete information than offline versions. Moreover, the approach of using an online survey is in line with data collection methods employed by other researchers within the m-health context (e.g. Andrews, et al., 2013; Whetstone & Goldsmith, 2009; Cho, et al., 2014).

The target sample included German citizens senior to age 18, of all health orientations, physical conditions and degrees of experience with m-health technologies. No selection criteria other than German citizenship were applied regarding the eligibility of respondents, since it was the aim to identify drivers of m-health adoption intention across any random subject.

Consequently, data was collected online through a convenience sample with snowball sampling (similar to e.g. Eunjoo, et al., 2015; Andrews, et al., 2013), during the months of March and first week of April 2017. The link to the survey was sent to contacts at minimum legal age, of diverse occupation and geographic location in Germany. Simultaneously, I asked them the favour to share it within their social circles, especially with their families to also reach respondents of higher ages. All questionnaire's items were required fields, so that respondents could not move on without answering all questions of a section. This was in line with research conducted by Albaum, et al. in 2010, who did not find any evidence for the impact of forced answering on completion rates.

Based on the assumption that everyone personally contacted shared the survey link with on average 2 people, it is estimated that in total 1000-1300 persons were reached. In response, 295 questionnaires were completed, resulting in a response rate of roughly 40 percent. This response rate is atypically high; probably a result of tapping the full potential of personal contacts who are more likely to do the favour of responding to the survey. Ilieva et al. (2002) discuss different findings on response rates of web and email surveys; a response rate of 30% seems typical. Of the 295 responses collected, 289 remained after removing inconsistent or ambiguous replies. An interesting observation that was made during the distribution of the survey was the fact that many respondents were very concerned about anonymous treatment of the survey as they were checking back for confidentiality before replying to the questions, therewith emphasizing the sensibility of the topic.

The collection of responses through hard copies was unfortunately not successful. I had attempted to collect responses in the radiology department of St. Josefs-Hospital Rheingau, but not even one response had been obtained. Initially, patients were personally approached and asked to fill in the survey during their waiting time, but from 18 approached patients, all refused to participate. It has to be taken into account that patients are concerned with their afflictions and thus might not have a free mind to think about something else. Further, I presume that the setting of a hospital frightened the people to provide personal data, despite reassurance of anonymity's preservation. I had wished to collect responses in another place through personal questionnaires, but because I was not present in Germany and time was limited, it was unfortunately not possible.

4.3 Research Design

The aim of this work is to examine which factors, and to what extent, influence consumer's intention to adopt m-health technologies. Based on literature's findings, a research model was developed in section 3.3. Consequently, to examine whether the hypothesized relationships between the latent variables are accurate, Partial Least Squares-Structural Equation Modelling (PLS-SEM) will be applied on the 289 responses collected. Therefore, the Software SmartPLS (v.3.2.6) was used (Ringle, et al., 2015).

In general, Structural Equation Modelling (SEM) is a combination of factor analysis and multiple regression; it aims to make predictions on the dependent variable (here, Behavioural Intention) from latent variables (e.g. Performance Expectancy), which are factors determined by several quantifiable variables (e.g. the measurement of Performance Expectancy through four items in the questionnaire) (Tabachnik & Fidell, 2007). It typically consists of two components: The *measurement model* relates the measured variables to the factors. The *structural model* describes the hypothesized causal relationships between the constructs, which are illustrated by paths, e.g. influence of PE on BI (Tabachnik & Fidell, 2007).

Within SEM, variance- and covariance-based approaches exist (Tabachnik & Fidell, 2007). PLS-SEM, the variance-based approach, is a causal modelling approach. It is to be preferred over covariance approaches when prediction and not confirmation of structural relationships are the research's objectives (Hair, et al., 2011) as it is the case in this study. Further important characteristics of PLS-SEM are its aim to maximize the explained variance of the dependent latent constructs as well as its application regardless of underlying distribution nor minimum sample size (Hair, et al., 2011). At the same time, Hair, et al. (2014) note that one needs to be mindful of sample size in relation to the underlying data characteristics and research model. For this work, recommended minimum sample size for a statistical power of 80% at a significance level of 1% has been met (Hair, et al., 2014, p. 21). Moreover, PLS-SEM is an established approach for business research, and superior to PLS regression when evaluating cause-effect relationships (Hair, et al., 2011) as it is the case for this work.

Finally, PLS is appropriate to use when collinearity between the independent variables is likely (Wold, et al., 1984), as it might be the case for Performance Expectancy and Effort Expectancy. For this reason, as well as the relatively small sample size, its ability to work with ordinal (quasi-metric) scaled data (Hair, et al., 2014) and robustness concerning slightly skewed data, PLS-SEM has been chosen. This approach is congruent with approaches used by other researchers studying m-health factors (e.g. Sun et al. 2013; Gao et al., 2015).

To analyse the data, a two-step approach is deployed, following Anderson & Gerbing (1988). During the first stage, reliability and validity of the measurement model were assessed, to determine the quality and appropriateness of the constructs used. In a second step, constructs and their significance are tested for, to evaluate the predictive power of the structural model.

5. Results

To analyse the results, first a preliminary analysis will be conducted, where the sample's characteristics will be described and the six questions exploring the status quo in m-health adoption in Germany analysed. Following, the proposed research model will be tested for reliability and validity, before the path's coefficients and the models' predictive power are subsequently examined. Finally, a discussion will conclude on the findings and discuss their meaningfulness.

5.1 Preliminary Analysis

5.1.1 Descriptive Statistics

Analysing the sample's characteristics (Table 1), it has to be noted that the sample is slightly imbalanced as it consists of 60% female and 40% male respondents. Following research pursued by Berens, et al. in 2016 on health literacy among different age groups in Germany, the sample was structured into different age groups. With a slight modification to the work of Bansal et al. (2016), four groups were defined: The first consisted of 'youth' aged 18-25, making up for 32% of the sample. The second group 'young adults' comprised of people aged 26-45, accounting for roughly 32,5%, just as did the third group of respondents, named 'adults' and aged 46-64. Seniors were defined aged 65 and older and represented 3%. Overall, this resulted in a mean age of 38 years. Almost everyone who participated in the survey indicated that he/she possessed a smarthphone and/or tablet, as 277 respondents (96%) confirmed.

Table 1: Sample Characteristics

Measure	Item	Frequency	Percentage
Gender	Male	171	59,17%
	Female	115	39,79%
Age	18-25	92	31,83%
	26-45	94	32,53%
	46-64	95	32,87%
	>=65	8	2,77%
Smartphone/Tablet Ownership	Yes	277	95,85%
	No	12	4,15%

Regarding the frequency of prior experiences with m-health technologies, thus questions 5-10 of the questionnaire, diverse observations can be made. It is worth to note that Likert Scale data is very subjective, in the sense that distances between the responses are not measurable, thus it is inaccurate to assume that responses are equidistant (Sullivan & Artino, 2013; Tabachnik & Fidell, 2007). Consequently, the following observations on user's prior experience of m-health technologies should be treated with caution. Since the utilization of means for ordinal scales (such as Likert scales) is of limited value unless the data is normally distributed, the modal value is more appropriate when interpreting the results (Sullivan & Artino, 2013). The modal value is that value which occurs most frequently. Diagrams representing the frequency of answers given to each question can be found in Appendices 8-13. Following, first the modal value of the overall sample is presented and subsequently the value by the above-described age groups, to discuss whether differences can be found according to age.

Relating to *prior voluntary usage* of m-health technologies for wellness respectively fitness purposes, 128 respondents (44%) have never used them. Analysing the frequency of utilization in association of the different age groups, an almost even distribution ranging from never to sometimes was found. With age, the tendency to never have used fitness/wellness applications increased. Examining the experiences with m-health technologies for *medical purposes*, 259 respondents (90%) indicated that they have never utilized these. Surprisingly, the youngest group of respondents as well as the adult group were the ones who had the highest number of respondents who used medical technologies at least sometimes and often. Analysing the frequency of usage for *administrative purposes*, the results revealed that 276 of 289 survey participants (96%) never had utilized m-health technologies. The respondents who indicated previous experiences were sporadically distributed across ages.

Next, the survey had asked the respondents whether they felt that m-health technologies were known within their social circles, hence *awareness* was studied. Overall, renownedness of these applications was estimated around the middle, thus most people thought their social environment had at least heard of m-health technologies. Very surprisingly, awareness tendentially increased with age, meaning that with the older age groups, more people had answered that m-health technologies were known by their contacts.

Asking for the perceived *effectiveness* of using m-health technologies, the vast majority of the sample, 150 respondents, replied that they did not observe that these applications helped them to achieve their health goals. Hence, it has to be taken into account, that at least 128 respondents have never made use of m-health technologies; this might serve as an explanation. However, it would be interesting to study the relationship of prior usage and experience effects, but therefore a longitudinal study would be needed.

Finally, the questionnaire had asked the respondents for the perceived *security* when utilizing m-health technologies. It was attempted to find whether people with e.g. cardiac diseases would feel safer when having the option to monitor their blood pressure and other indicators. Similarly, people suffering from obesity might feel more in control when utilizing applications that track their physical activity as well as caloric intake more precisely. Interestingly, 98 people responded with Likert values equal and higher to 3, meaning that m-health technologies made them, at least to some extent, feel safer.

5.1.2 Scale Reliability

The following section presents now the tests that were performed to assess scale reliability and validity of the measurement model, thus whether the items that were measured through the questionnaire are appropriate. The methodology following and all explanations are based on Hair et al. (2014) unless otherwise indicated. Since it is impossible to directly measure e.g. PE, several indicators of PE were measured through the items in the questionnaire. The use of several items allows for a more accurate determination of the final construct. In cases where a construct (also factor) is determined by two or more variables, it is called a latent variable. Its value is not directly observable and thus alternatively measured through the questionnaire's items.

While PLS can work with reflective and formative models (Hair, et al., 2011), all constructs were modelled to be reflective. This approach is in line with others' works (e.g. Venkatesh et al., 2003; Dwivedi et al., 2016; Sun et al., 2013). A discussion on how to identify the right model is presented by Coltman, et al. (2008). Reflective constructs underlie the assumption of a causal relationship between the indicator and the latent construct, therefore the indicators must be correlated (Kummer, et al., 2017). In that sense, indicators should at least represent the majority of the content domain which the construct aims to measure. Further, reflective measurement models need to be examined for their validity and reliability.

For reflective measurement models, Hair, et al. (2014) suggest to assess the construct's *reliability* through composite reliability and/or Cronbach's alpha tests. Next, the measurement's model *validity* is to be assessed through convergent validity (measured through indicator reliability and average variance extracted) and discriminant validity (measured through cross loadings and the Fornell-Larcker criterion).

Construct reliability assessment

Internal Consistency Reliability is typically measured through *Cronbach's alpha* criterion. It calculates the intercorrelations between the observed indicator variables and thus estimates the reliability. The main underlying assumption is that all indicators are equally reliable, whereas PLS-SEM evaluates each indicator on its individual reliability and prioritizes accordingly. Since Cronbach's alpha is said to typically underestimate reliability, it can be used as a very conservative tool. An alternative measure is *composite reliability*, which takes the outer loadings of the indicator variables into account. In exploratory researches, a value of 0.6 to 0.7 is acceptable and between 0.7 and 0.9 desirable. Critical values are those that are below 0.6, as they suggest a lack of internal consistency, as well as values over 0.95, as they indicate that all indicator variables do measure the same. (Hair, et al., 2014).

Results

Analysing the results (Table 2), all values for composite reliability were above the threshold of 0.7. However, Composite Reliability exceeded the threshold of 0.95 for BI (0.96) and SI (0.972). Following a discussion with one of the SmartPLS Developers[1] on how to proceed in these cases, the questionnaires' items for SI and BI were reviewed for redundancy of items. However, since the items were conceptually close but still different, and – interestingly – the measurement items for both constructs were adopted from Venkatesh et al. (2012) who have researched technology acceptance for several years and did not obtain similar indications, all of the item's constructs were retained.

The results for Cronbach's alpha, as the more conservative measure, were almost all above 0.7, with FC at 0.658. The higher the alpha, the higher is the covariance among the items – which is actually strived for, since higher covariance indicates that the items actually measure the same constructs – but not to the point of redundancy as mentioned above. As Hair et al. (2014) argue that composite reliability is more precise for assessing construct reliability, nothing is undertaken at this point concerning the comparably low alpha value for FC.

[1] Forum.smartpls.com: http://forum.smartpls.com/viewtopic.php?f=5&t=3805 [accessed: 03.05.2017]

Table 2: Results from the reliability and validity measurements

	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
BI	0,937	0,960	0,888
EE	0,908	0,935	0,783
FC	0,658	0,770	0,540
PE	0,882	0,918	0,738
PR	0,706	0,824	0,627
PS	0,846	0,884	0,562
SA	0,863	0,905	0,705
SE	0,917	0,947	0,857
SI	0,956	0,972	0,919

Reflective Measurement Models' Validity Assessment

Generally speaking, validity is assessed through convergent validity as well as discriminant validity.

"**Convergent validity** is the extent to which a measure correlates positively with alternative measures of the same construct" (Hair, et al., 2014, p. 102). Since it is the items' aim to measure the same construct, the indicators contributing to a construct should be highly correlated. Therefore, typically two measures are used: Indicator reliability as well as Average Variance Extracted (AVE).

Indicator reliability describes the commonalities shared by the indicators of a construct, the higher the outer loadings, the more associated they are. Standardized outer loadings should be at least 0.708.

AVE is used to establish validity on the construct level. It is defined as "[…] the grand mean value of the squared loadings of the indicators associated with the construct (i.e., the sum of the squared loadings divided by the number of indicators)" (Hair, et al., 2014, p. 104). An AVE of at least 0.5 suggests that half of the variance of the indicators is explained by the construct, else more error remains than variance is explained. Further, it should be assessed for each reflectively measured construct.

Results

Examining outer loadings (Appendix 14), FC1 (0.516), FC4 (0.461), PR1 (0.471) and PS2 (0.630) fall below the threshold. Hair, et al. (2014) urge to be careful in removing items just because they fall below 0.708, since the removal of an indicator might impact content validity. This implies that some items might, despite their low loading, be retained as they contribute to the content's validity.

Analysing AVE, the value for FC fell initially below 0.5. Going back to outer loadings, FC4 is close to 0.4, from which point onwards an indicator always needs to be removed from the construct (Hair, et al., 2014). Despite the fact that FC4 contributes content-wise to the construct of FC, it is removed, as consequently AVE is at 0.54, thus meeting the threshold (Table 2) and CR-α improved to 0.658 from initially 0.64. The items of PR1 and PS2 are retained, since their AVE values are above the threshold and they contribute content-wise to the construct's measurement.

"**Discriminant validity** is the extent to which a construct is truly distinct from other constructs by empirical standards" (Hair, et al., 2014, p. 104). In other words, each construct should contribute unique value to the model and shed light from a different perspective.

To examine the *Cross Loadings* of indicators, the indicator's outer loadings are compared to all of its loadings on the other constructs. The value between an indicator and its construct needs to be higher than to all other construct, to avoid discriminant validity problems occur. However, this happens quite often, causing this method's results to be often neglected.

A more cautious approach is the *Fornell-Larcker criterion* (Table 3), which assesses whether the variance between a construct's indicators and the construct itself is higher than between the construct and other constructs. This is fulfilled if the square root of the AVE of each construct is higher than the highest correlation with any other construct used.

Table 3: Fornell-Larcker Criterion

	BI	**EE**	**FC**	**PE**	**PR**	**PS**	**SA**	**SE**	**SI**
BI	0,942								
EE	0,226	0,885							
FC	0,458	0,572	0,735						
PE	0,646	0,296	0,425	0,859					
PR	0,086	0,059	0,075	0,091	0,792				
PS	0,330	0,092	0,102	0,365	0,288	0,749			
SA	0,306	0,097	0,090	0,293	0,392	0,673	0,839		
SE	0,318	0,780	0,669	0,303	0,000	0,138	0,165	0,926	
SI	0,574	0,178	0,334	0,586	0,032	0,249	0,225	0,211	0,959

Results

All indicator variables satisfied the cross loadings criterion as well as the Fornell-Lacker criterion. Consquently, after removing the indicator variable FC4 from the FC construct, the measurement model fulfills all criteria for validity and reliability. Next, the structural equation model will be assessed.

5.2 Findings on PLS-SEM

After the measurement model was confirmed through the various reliability and validity tests in 4.1, this section will now explore the model's predictive power as well as the relationships between the constructs.

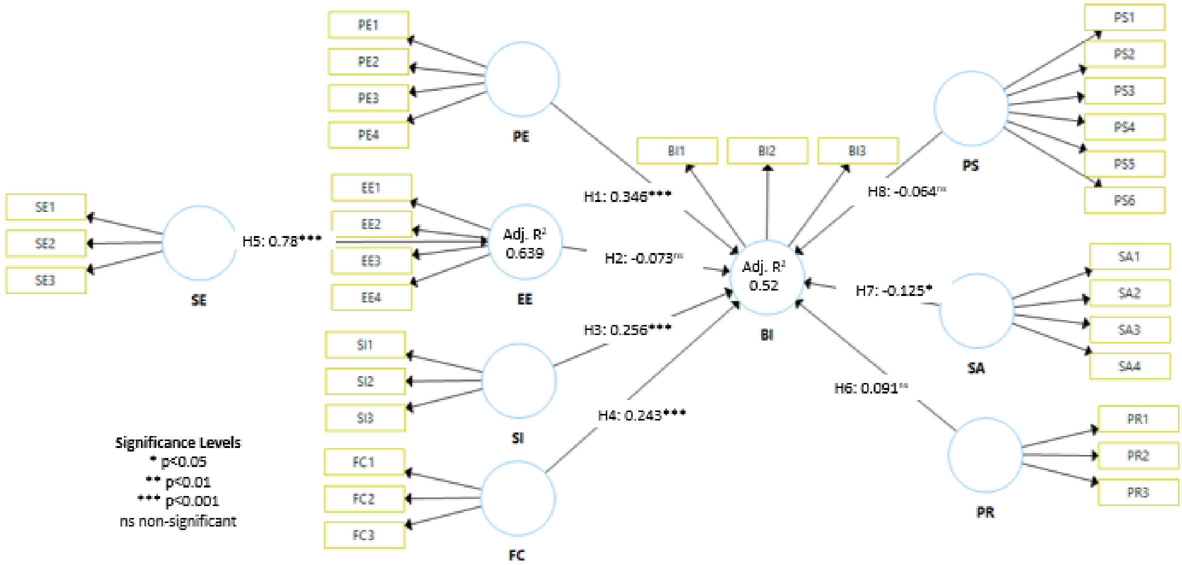
First, collinearity needs to be tested for since the path coefficients are calculated on OLS regressions of the endogenous variables and might be biased, if multicollinearity among the constructs occurs. Indicators of collinearity are Variance Inflation Factor (VIF) values above 5 (Hair, et al., 2014). All model's inner VIF values were far below 5, with the highest of SA at 2.027. Consequently, collinearity is not an issue.

Next, significance levels need to be examined. For researches related to Marketing, typically a significance level of 5% is applied (Hair, et al., 2014). The effects of FC, PE, SE and SI on BI are significant at a level of $p < 0.001$. The construct of SA is significant at a level of $p<0.05$. EE, PR and PS are statistically not significant, as their p-values measure 0.064, 0.056 and 0.131 respectively. Consequently, the hypotheses H1, H3, H4, H5 and H7 show a good fit for the data and thus are not rejected, while hypotheses H2, H6 and H8 need to be rejected. The probability for incorrectly rejecting the Null Hypothesis is too high.

Next, the path coefficients of the Structural Model could be estimated. The standardized values of the paths directing from the exogenous to the endogenous variable range between -1 (strong negative relationship) and +1 (strong positive relationship), with coefficients closer to 0 indicating weaker relationships. The path coefficients from the PLS can be interpreted the same way as beta values from OLS regression (Henseler, et al., 2009). To assess the values, a bootstrapping procedure was applied and the results are shown in Figure 5. The strongest relationship was found from SE on EE (β=0.78***), and PE on BI (β=0.346***), SI on BI (β=0.256***) and FC (β=0.243***). EE(β=-0.073^{ns}), SA (β=-0.125***), PS(β=-0.064^{ns}) showed rather weak and negative, respectively PR(β=0.091^{ns}) weak and positive relationships.

Finally, R^2 is the coefficient that measures the model's predictive power as it depicts the combined effects of the exogenous variables on the endogenous variable (Hair, et al., 2014). Chin (1998) states that R^2 values of 0.19 are considered weak, 0.33 moderate and 0.67 substantial. Hair et al. (2014) note that in consumer behaviour research, R^2 values of 0.2 and above are considered as high. The research model of this work has a R^2 value of 0.532, respectively adjusted R^2 of 0.52 for behavioural intention and R^2 of 0.642, respectively adjusted R^2 of 0.639 for EE. The adjusted R^2 value is more meaningful, as it considers the number of exogenous constructs and sample size into account, therewith improving the comparability of R^2 measures. Despite the fact that the R^2 for BI is not yet considered to be substantial, also lower r-squares contain interesting information on relationships and can still be useful. A lower score simply means that there are other factors that affect the dependent variable.

Figure 5: Structural Model with Path Coefficients and Significance Levels



To assess the predictive relevance (Q^2) for the path model, the blindfolding procedure was additionally applied. For each endogenous variable, the measure delivers cross-validated redundancy measures. Any value higher than 0 indicates that the exogenous constructs have predictive relevance for the endogenous variable. Q^2 values of 0.02, 015 and 0.35 indicate small, medium and large predictive power of the exogenous variables on the endogenous ones. (Hair, et al., 2014) In the model at hand, Q^2 (BI) equals 0.438 and Q^2 (EE) equals 0.446. Consequently, the exogenous variables embedded in the research model have predictive relevance for BI.

5.3 Discussion

The results from the PLS-SEM analysis confirm several highly significant and positive relationships on BI which are in line with prior works, thus evidence is found for the manifestation of their strong influence. The predominant effect of Performance Expectancy on Behavioural Intention with PE's path coefficient of 0.346 at a highly significant level ($p<0.001$) has been sustained. This result corresponds to outcomes of e.g. Venkatesh, et al., 2003; Lim, et al., 2011; Hu, et al., 1999. Further, Self-Efficacy as a predecessor of Effort Expectancy has also proven to be highly significant ($p<0.001$) and to have a strong positive relationship on BI ($\beta=0.78$). Consequently, the belief oneself has on how well he can operate a technology (SE) strongly influences the perception on how much effort (EE) will be needed to use a m-health technology. This evidence is in line with research conducted by Venkatesh & Davis in 1996. Facilitating Conditions and Social Influence, other constructs of the original UTAUT model, have been validated with strong positive and significant relationships on BI ($p<0.001$), corresponding to other researcher's findings in the m-health area, e.g. Dwivedi et al. (2016). Since especially SI is usually higher for technologies that are emerging and not yet widely spread (Venkatesh & Davis, 2000), the moderate positive impact of SI on BI can be justified. To subsume, the direct effects of PE, SI and FC on BI have been confirmed and should be used throughout future research. The remaining construct of the original UTAUT model, Effort Expectancy, is found to be insignificant. This result is not too much surprising, since several prior works have found an insignificant effect of EE on BI for m-health studies (e.g. Yuan et. al, 2015; Cho et al., 2014).

Following a comment of Featherman & Pavlou (2003), that future research should focus more on potential losses from adopting e-services, the three constructs of Surveillance Anxiety (SA), Physical Risk (PR) and Perceived Security and Privacy Risk (PS) were added to complement technology acceptance models from a risk perspective, and were postulated as negatively affecting BI as formulated in H6, H7 and H8, respectively.

The effect of SA is significant ($p<0.05$), and, as expected, has a negative influence on Behavioural Intention ($\beta=-0.125$). This result goes hand in hand with research conducted by Spiekermann (2008), who reports that Surveillance Anxiety, next to Information Collection, is one of the predominant concerns of German consumers using RFID equipment. Since Kummer et al. (2017) are one of the few researchers who also included the construct of Surveillance

Anxiety for adoption of sensor-based health equipments but did not find a significant effect, this construct requires further investigation and inclusion to future research models.

The other two constructs, PR and PS, did not render significant impacts. PR, a construct that had been newly added to technology acceptance studies, was adopted from Stone & Grønhaug (1993). Since this construct had never been included in technology acceptance studies, but was expected to have an influence on BI escpecially in a healthcare context, it was included. The expectation was that people, using m-health technologies instead of personally seeing a doctor, might be afraid to suffer physical risks in the sense that they do not detect illnesses a physician might have discovered. However, PR had not been found to be significant. One explanation might be that users trust the system due to surveillance and monitoring options enough, to not be exposed to a risk. Further, as one of the items had asked for the fear of overmonitoring, thus obsessing with health data, and many people had indicated to not frequently use m-health technologies, or if so, for fitness/wellness purposes, for which suffering physical risk is less likely, another justification might be found.

The most puzzling result however was the insignificance of Perceived Privacy and Security Risks. Since m-health technologies treat highly confidential and private data, and technology is often subject to hacker attacks, it was expected that privacy and security concerns would significantly and negatively impact m-health adoption intention behaviour. Shareef et al. (2014) had identified a meaninful relationship between perceived privacy/security and attitude to use m-health. One explanation for the not significant path coefficient might be that users do not have any concerns since most of them do not (often) use m-health technologies, and if they do, most of them have used it for fitness/wellness purposes. Possibly this kind of information is not perceived to be very confidential, since those applications most often measure e.g. food intake and physical activity. As seen in 4.1.1 only 30 respondents of the sample have ever tried m-health for medical purposes and even less people for administrive issues, which are considered to contain more private information.

6. Implications and limitations

This work aims to identify factors that drive consumer's intention to adopt m-health technologies. Starting with a literature review on prevalent technology acceptance theories, constructs from the UTAUT model were complemented with constructs that might prevent technology adoption intention. To examine the model's predictive power, a sample of 289 respondents was obtained through an online survey. Through PLS-SEM, the data was examined for reliability and validity, and returned an adjusted R^2 value of 0.52.

6.1 Theoretical Implications

Besides the application of well-founded factors like PE, EE, SI and FC from the UTAUT model, that have been very often utilized in technology acceptance research, factors for potential losses like SA, PR and SE have been included. The combination of these factors as such was completely new. The strongest predictors of BI, in descending order, are PE, SI, FC as well as SA. Further, the constructs of the UTAUT model have been mostly confirmed enhancing the suitability of the model in a healthcare context. This is relevant as most of the studies have either adopted TAM as a foundation (e.g. Lanseng & Andreassen, 2007; Lim, et al., 2011; Cho, et al., 2014) or combined several other models (e.g. Sun et al., 2013). Further, Surveillance Anxiety should be included in future research, especially on German consumers, while the construct of Perceived Security and Privacy needs further examination. Moreover, it is one of the few models that focuses on the adoption intention of consumers and not that of professionals (e.g. Bhattacherjee & Hikmet, 2007). Last but not least, the study contributes to the exploration of consumers' determinants in Europe (next to Kummer et al., 2017; Whetstone & Goldsmith, 2009; Lanseng & Andreassen, 2007) since, as mentioned in the introductory note, the majority focuses on the Asian continent.

6.2 Practical Implications

As Performance Expectancy has been found to be the strongest predictor of behavioural intention, consumers' motivation to adopt m-health technologies seems to be driven by utilitarian values. Therefore, m-health marketers need to focus on strongly communicating the benefits of utilizing m-health technologies. Thus, characteristics such as higher efficacy and improved monitoring of the user's health condition should be stressed just as much as the higher level of convenience. Further, consumers should be reassured that they possess the necessary knowledge and skills to use m-health technologies in daily life, thus providing support services for learning how to use m-health technologies might promote consumer's perceived Self-Efficacy. In addition, the establishment of a generally positive perception, thus targeting early adopters and fostering word-of-mouth is premise, as social influence will strongly drive consumers' acceptance. Last but not least, consumers need to be in power of deciding what exactly is recorded and saved, as surveillance anxiety is prevalent. Practitioners should also be aware, that behavioural intention is not more than a proxy measuring technology's acceptance, that is to say that a positive BI does not yet confirm actual usage of a technology. Studies have shown that there are significant differences between BI and actual usage (e.g. Lim, et al., 2011). Eventually, the research shows that m-health technologies have not yet widely dispersed, as 44% of the sample have never used them, which is remarkable in the face of certain health apps being standardly installed on smartphones and frequently record data, as through a pedometer, in the background.

6.3 Limitations and Future Research

While several determinants of the proposed research model have been found to be statistically significant and the results contribute to theory and practice, several limitations must be considered. The data that formed the basis for empirical validation was collected through a convenience sample, thus, despite the attempt to obtain results from users of different educational backgrounds, technology affinity levels and health conditions, a slight bias cannot be totally excluded. Moreover, the sample was not absolutely balanced, as it had a minor propensity towards female (60%) and younger (46% were aged below 30) respondents. Additionally, this research gathered evidence exclusively through an online survey, which is, according to e.g. Ilieva, et al. (2002) not inferior to offline data collection, however a multimode approach, as attempted, could verify the equality of findings. Eventually, since quantitative studies often require Likert scales as measurements, individual differences and perceptions get lost, inducing potential investigations of determinants through qualitative measures.

While this study had deliberately depicted m-health technology acceptance on a general level to represent the status quo of ordinary perceptions of these applications, future research could include product type (e.g. fitness/medical device) as a moderator effect. Therewith, the effect of perceived privacy and security and the possible explanation that its' relationship on BI for fitness and wellness devices can be neglected, should be verified. The results could provide support for Gao et al.'s (2015) findings that depending on product type, different determinants are more and less relevant for predicting BI. Further, a longitudinal study could account for an experience effect and measure actual usage, and both their impacts on BI. At large, it is indispensable to pursue further research on determinants that drive consumers' acceptance in Europe as well as to contrast cultural effects through e.g. a comparative study among different cultures.

7. Conclusion

This work attempted to extend the UTAUT model for constructs of potential losses, which were expected to negatively impact consumers' intention to adopt mobile health technologies. The original model was modified to the extent that Self-Efficacy was added as a predecessor of Effort Expectancy, as well as the constructs of Surveillance Anxiety, Physical Risk and Perceived Privacy and Security Risk as determinants for Behavioural Intention, to account for impeding factors. The moderating effects of age, gender and experience had been removed. Further, this work explored the current disposition of German consumers towards the adoption of mobile health technologies.

Empirical evidence gathered from 289 consumers and analysed through PLS-SEM showed support for the application of the UTAUT model in a consumer and healthcare context. The results revealed Self-Efficacy to be a very powerful determinant for Effort-Expectancy, while Performance Expectancy has the strongest influence on Behavioural Intention to adopt m-health technologies. Subsequent significant determinants, ordered according to their effects on Behavioural Intention are Social Influence, Facilitating Conditions and Surveillance Anxiety. Consequently, utilitarian motives should be communicated and early adopters addressed through appropriate measures, as to exploit social influence and trigger adoption. Simultaneously, it is essential to persuade users of their ability to use mobile health technologies and offer respective support and service. According to the obtained results, potential risks to be suffered physically as well as in terms of privacy and security do not play an important role in attempting to adopt mobile health technologies. As suggested, future research should investigate whether these results are generalizable or maybe moderated by products for wellness/fitness purposes.

Overall, the suggested model has a predictive power of adjusted R^2 of 0.52 and the modelled exogenous variables priorly discussed have predictive relevance for Behavioural Intention with a Q^2 for BI equal to 0.438. Therewith, it contributes to the understanding of determinants that drive consumers' intention in adopting mobile health technologies and complements current findings with the construct of Surveillance Anxiety. Eventually, the presented work adds to research targeted to investigate consumers' behaviour in Europe and should motivate future studies, since digital offerings are likely to gain traction. Mobile health technologies present huge opportunities for both, actors within the healthcare industry through the enablement of better medical outcomes due to improved patients medication adherence, cost-efficiencies and remote supervision, as well as consumers as they are directly engaged in managing and contributing to their health condition. To ride the crest of the wave, pharmaceutical companies should rethink their business models and foster partnerships with technology firms, as this collaboration will enable them to offer what patients need next.

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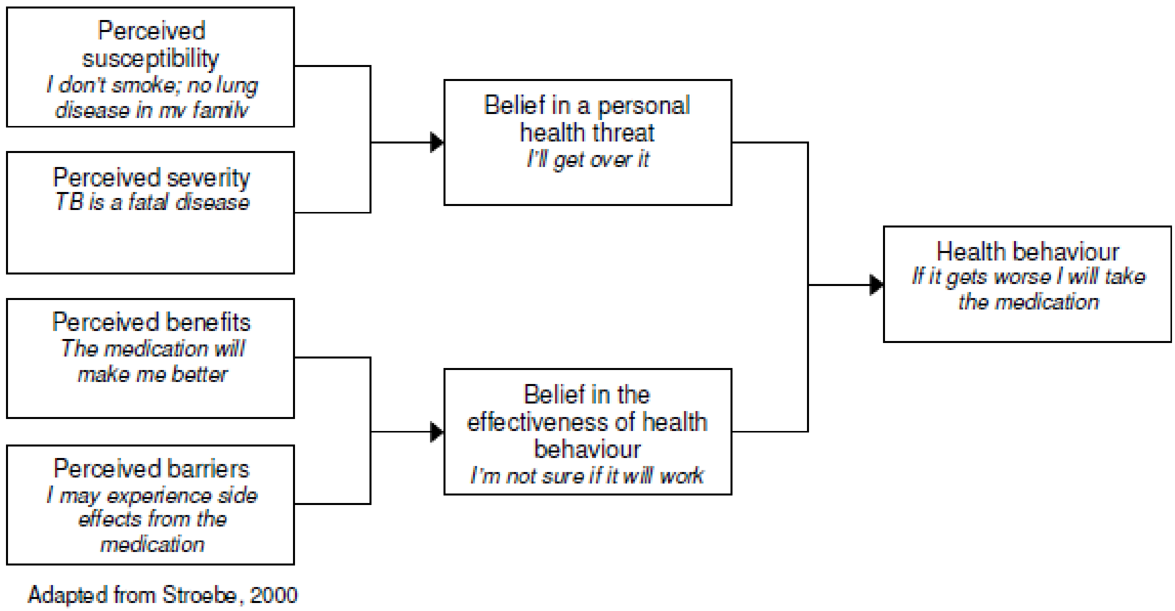
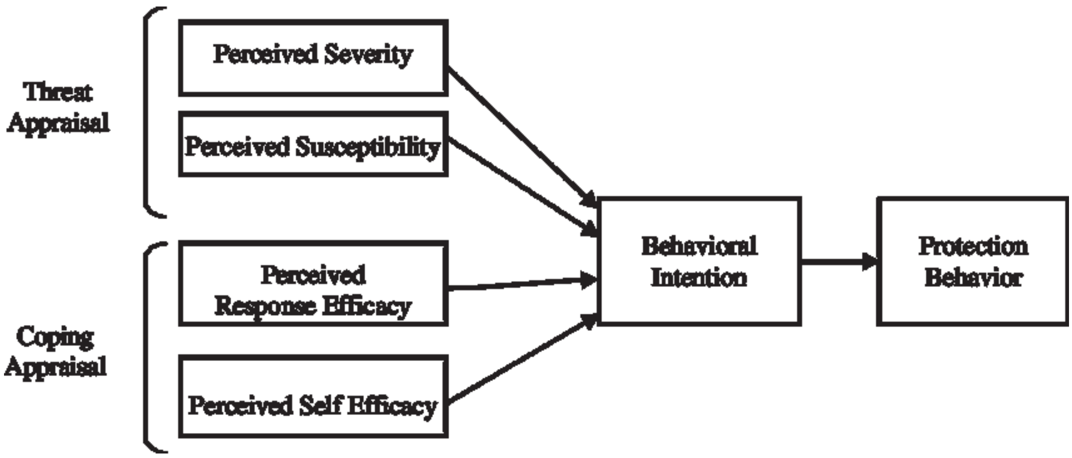
Appendices

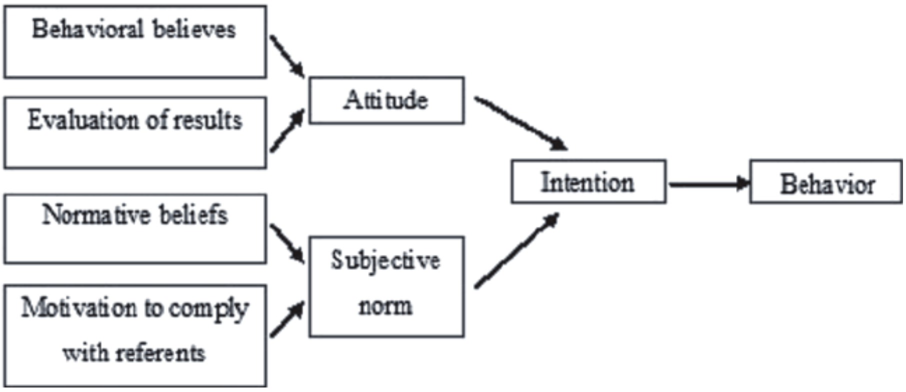
Appendix 1: Health Belief Model (as in Munro et al., 2007)



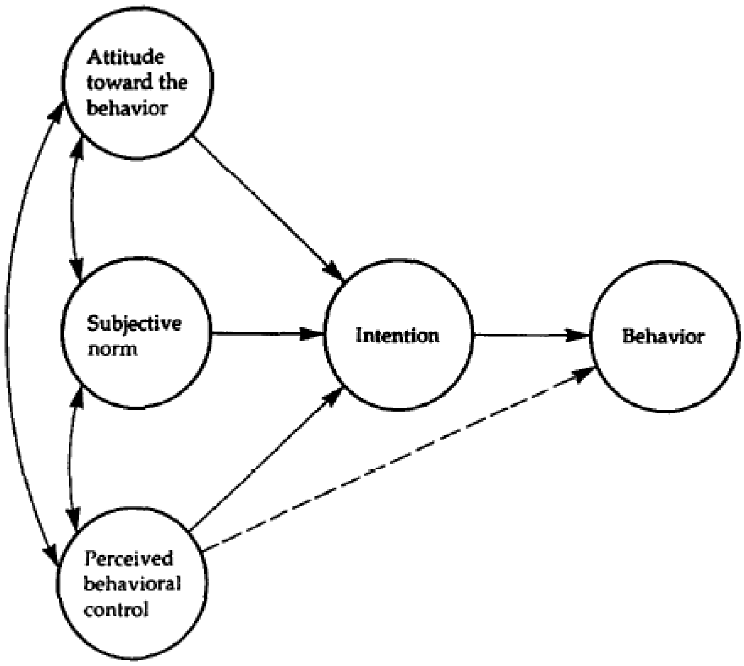
Appendix 2: Protection Motivation Theory (as in Lwin, et al., 2012)



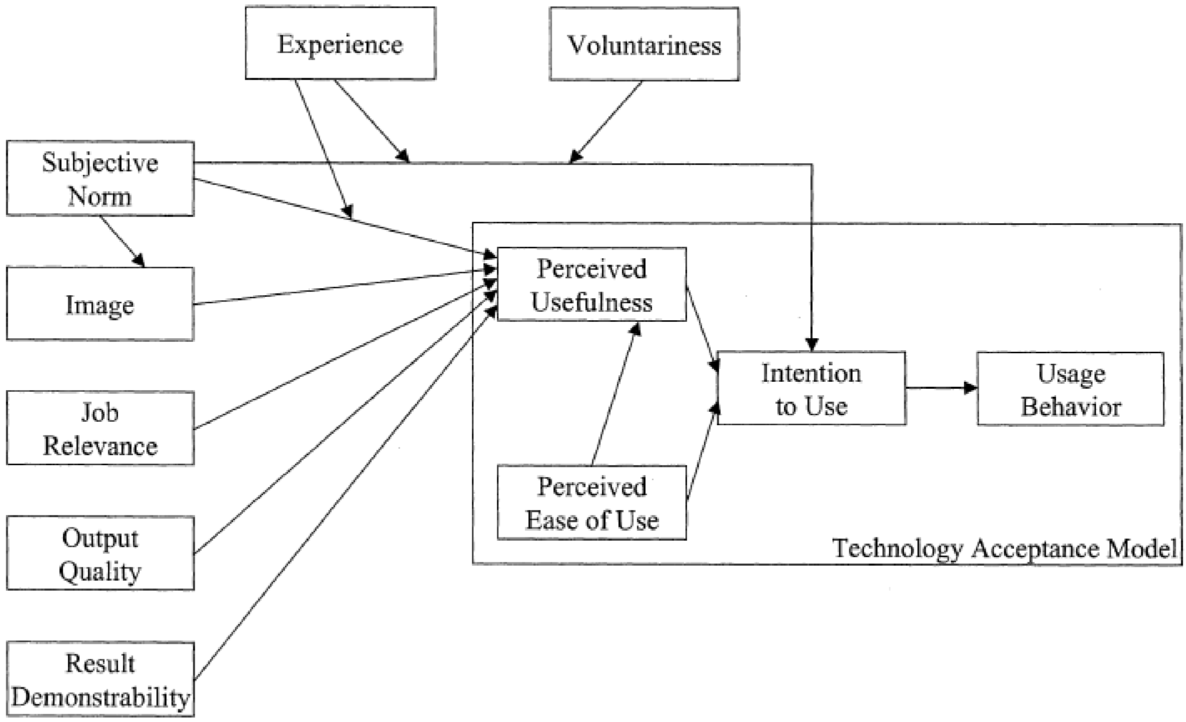
Appendix 3: Theory of Reasoned Action (as in Fishbein and Ajzen, 1975)



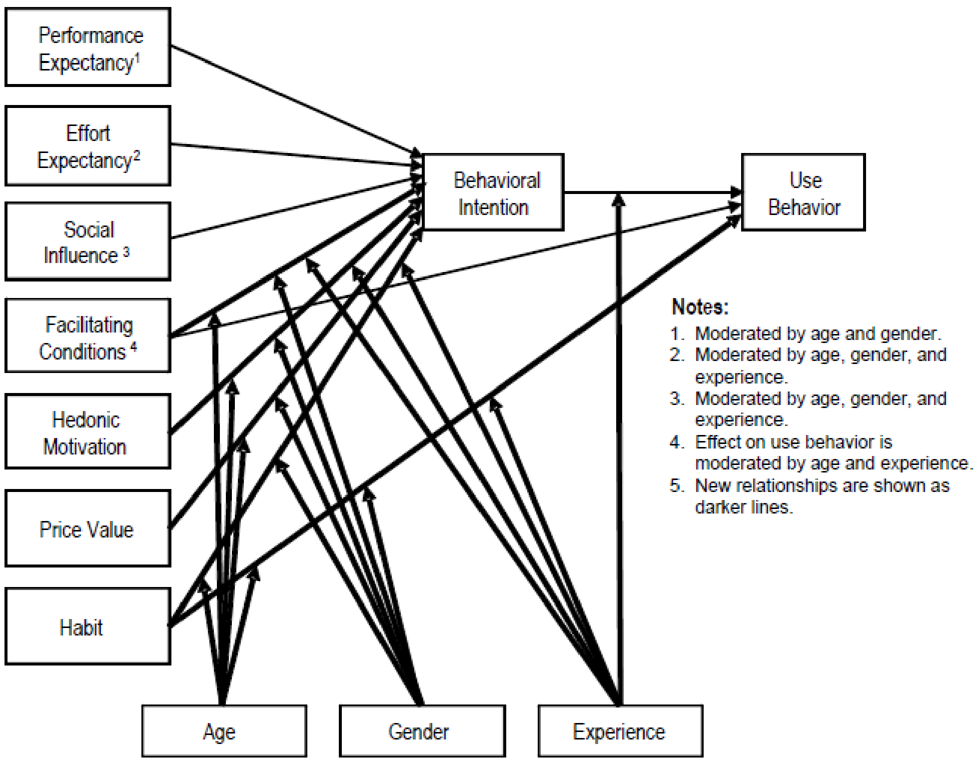
Appendix 4: Theory of Planned Behaviour (as in Ajzen, 1991)



Appendix 5: Extended Technology Acceptance Model, TAM2 (Venkatesh & Davis, 2000)



Appendix 6: UTAUT2 Model, Venkatesh et al., (2012)



Appendix 7: Questionnaire

Thank you very much for participating in the following survey about m-health technologies. The research is part of a master thesis examining factors which influence the adoption of m-health technologies from a consumer's perspective in Germany. Your insights and opinion on m-health will shed light on determinants for adoption and give researchers and managers the opportunity, to adjust their offering accordingly.

M-health refers to the usage of mobile technologies such as smartphones, tablets, wearables and other RFID equipment to track and monitor the health status. Typically, sensors (e.g. in a wristband or implemented in the user's body) measure changes in the physical condition of the user (patient). These changes are continuously transmitted to the user's smartphone/tablet, where they are monitored, recorded and analysed. In case of medical devices, the information is simultaneously wirelessly transmitted to medical professionals, who can remotely make an analysis.[2]

Functionalities include, but are not limited to: "Transmission of electronic medical records between medical staff and patients, monitoring patients remotely, sending electronic alerts for disease control [and reminders for medicine intake], and providing useful applications, information, and functionality to health consumers."[3]

Responding to the survey will take approximately 12 minutes. All information collected is completely anonymous and will exclusively be used for statistical purposes of this master thesis.

In case of questions, comments and any other remarks, please do not hesitate to contact me: alexandra.dzimiera@edu.escpeurope.eu

General questions

Q1: Please indicate your gender: (Female/Male)

Q2: How old are you? (open question)

Q3: Do you possess a smartphone or a tablet? (Yes/No)

Q4: Are you a German citizen? (Yes/No)

In this short section, please indicate your previous experiences with m-health technologies on a scale from 1 (never) to 5 (very often)

Q5: Do you use m-health technologies voluntarily for fitness/wellness purposes?

Q6: Do you use m-health technologies for medical purposes, e.g. blood pressure monitoring, blood sugar measurement?

Q7: Do you use m-health technologies for administrative purposes, e.g. patient data exchange?

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[2] Adapted from Dwivedi et al., 2016, "A generalised adoption model for services: A cross-country comparison of m-health (m-health)", Government Information Quarterly, Vol. 33, p. 174-187

[3] Rai et al., 2013, "Understanding Determinants of Consumer M-health Usage Intentions, Assimilation, and Channel Preferences", Journal of Medical Internet Research, Vol. 8

Q8: Are you under the impression that m-health technologies are widely known in your social environment?
Q9: How much have m-health technologies helped you to achieve your health goals?
Q10: Do m-health technologies give you more security regarding your health status?

Structural Equation Model

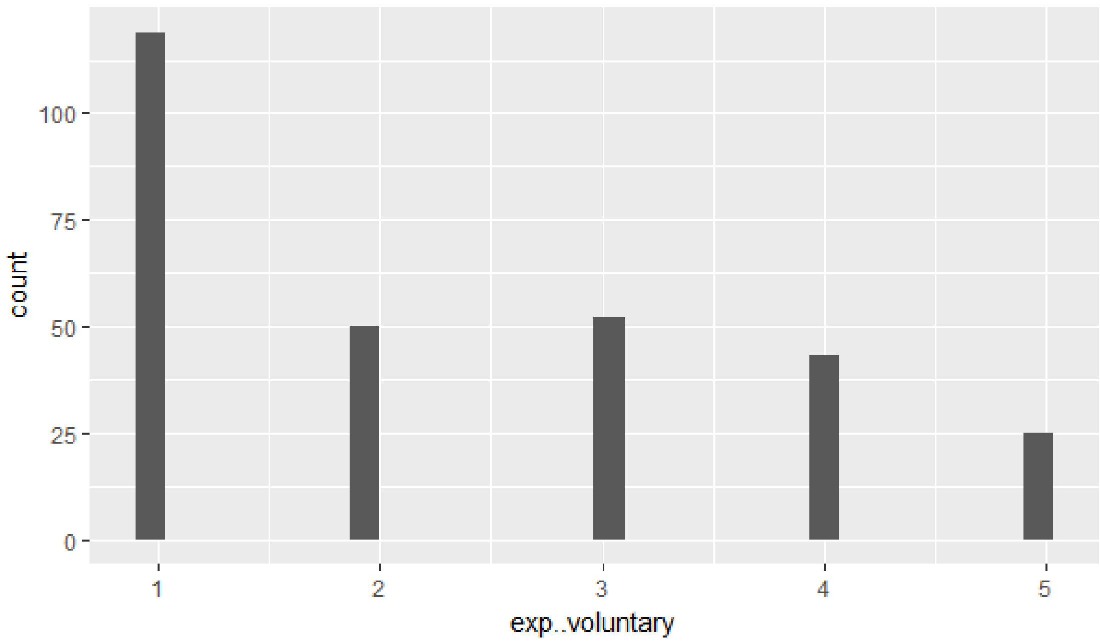
Please rate the following statements according to your opinion on a scale ranging from 1 (strongly disagree) to 5 (strongly agree). In case you have not yet used m-health technologies, please rate according to your expectation/general perception.

Determinant	*Adapted from:*
Performance Expectancy/Perceived Usefulness	
PE1: Using m-health technologies will help me to better observe my health condition.	Venkatesh et al., 2012
PE2: Using m-health technologies will make my life more convenient.	Sun et al., 2013
PE3: Using m-health technologies will make me more effective in managing my health.	Goldsmith and Whetstone, 2009
PE 4: Overall, I would find m-health technologies to be useful in my life.	Sun et al., 2013
Effort Expectancy/Perceived Ease of Use	
EE1: Learning how to use m-health technologies is easy for me.	Venkatesh et al., 2012
EE2: My interaction with m-health technologies is clear and understandable.	Venkatesh et al., 2012
EE3: I think m-health technologies are easy to use.	Venkatesh et al., 2012
EE4: It is easy for me to become skilful at receiving, monitoring and interpreting health-care data through m-health technologies.	Dwivedi et al., 2016
Social Influence	
SI1: People who are important to me think that I should use m-health technologies.	Venkatesh et al., 2012
SI2: People who influence my behaviour think that I should use m-health.	Venkatesh et al., 2012
SI3: People whose opinions I value prefer that I use m-health technologies.	Venkatesh et al., 2012
Facilitating Conditions	
FC1: I have the secured and trusted resources necessary to use m-health technologies.	Dwivedi et al., 2016
FC2: I gathered the knowledge necessary to use m-health technologies.	Dwivedi et al., 2016
FC3: M-health technologies are compatible with my daily routine.	Dwivedi et al., 2016
FC4: I can get reliable help from medical or technical professionals when experiencing difficulties using m-health technologies.	Dwivedi et al., 2016

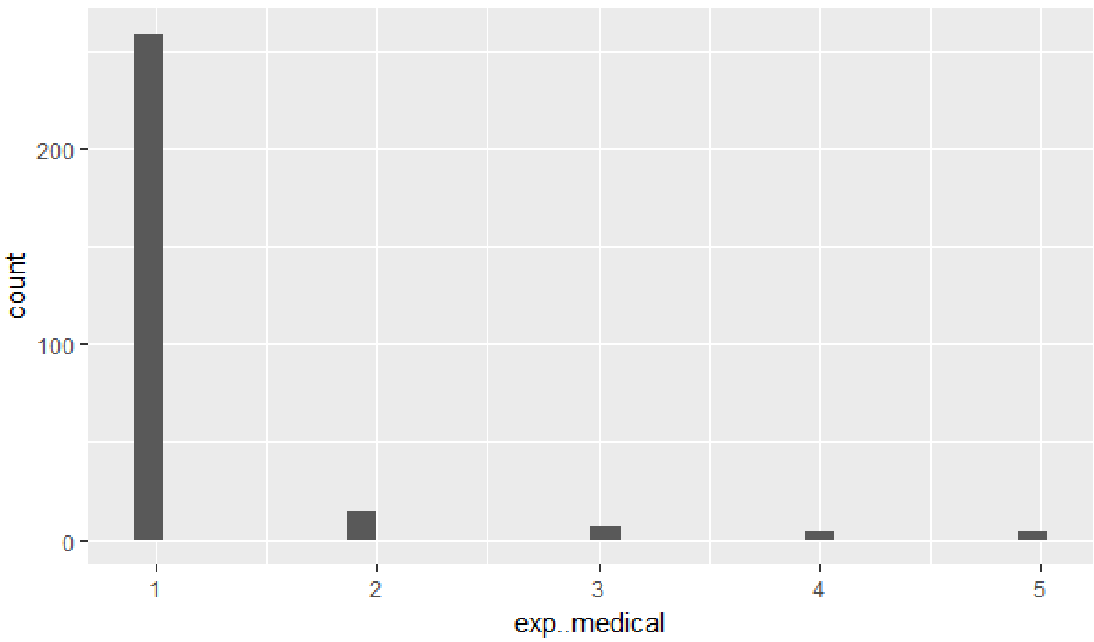
Self-Efficacy	
SE1: It is easy for me to use m-health technologies.	Sun et al., 2013, adapted from Johnston et al., 2010, Lee et al., 2009
SE2: I have the capability to use m-health technologies.	Sun et al., 2013, adapted from Johnston et al., 2010, Lee et al., 2009
SE3: I am able to use m-health technologies without much effort.	Sun et al., 2013, adapted from Johnston et al., 2010, Lee et al., 2009
Physical Risk	
PR1: One concern I have about using m-health technologies is that I could overuse the technology, in a sense of over-monitoring.	Stone & Gronhaug, 1993
PR2: Because m-health technologies may not completely replace personal contact with a doctor, I become concerned about suffering potential physical risks from using technology instead of seeing a doctor.	Stone & Gronhaug, 1993
PR3: Because m-health technology may not be completely safe, I become concerned about potential physical risks associated with these products.	Stone & Gronhaug, 1993
Surveillance Anxiety	
SA1: The idea that I would be under surveillance frightens me.	Kummer, Recker, Bick, 2017
SA2 I find it objectionable when I do not know what will be recorded.	Kummer, Recker, Bick, 2017
SA3 It would bother me that others see my health behaviour and health status.	Kummer, Recker, Bick, 2017
SA4 It disturbs me that the system permanently monitors me.	Kummer, Recker, Bick, 2017
Perceived privacy and security	
PS1: I believe healthcare service from remote place through m-health technology is not safe.	Shareef et al,2014
PS2: I think the concerned provider does not take full responsibility for any type of insecurity for the usage of m-health technologies.	Shareef et al,2014
PS3: I would hesitate to provide the recorded information through the usage of mobile technology to the provider.	Shareef et al,2014
PS4: I believe the technology provider might share my personal information which is collected through the used m-health technology with others.	Shareef et al,2014
PS5: I believe my personal data which is collected through the used m-health technology is not protected against such risks as loss or unauthorized access, use, destruction, modification, or disclosure.	Shareef et al,2014

PS6: I believe my personally identifiable health information which is collected through the used m-health technology might be disclosed without my authorization.	Shareef et al,2014
Behavioural Intention to Adopt	
BI1: I intend to use m-health technologies in the future.	Venkatesh et al., 2012
BI2: I will always try to use m-health technologies in my daily life.	Venkatesh et al., 2012
BI3: I plan to use m-health technologies frequently.	Venkatesh et al., 2012

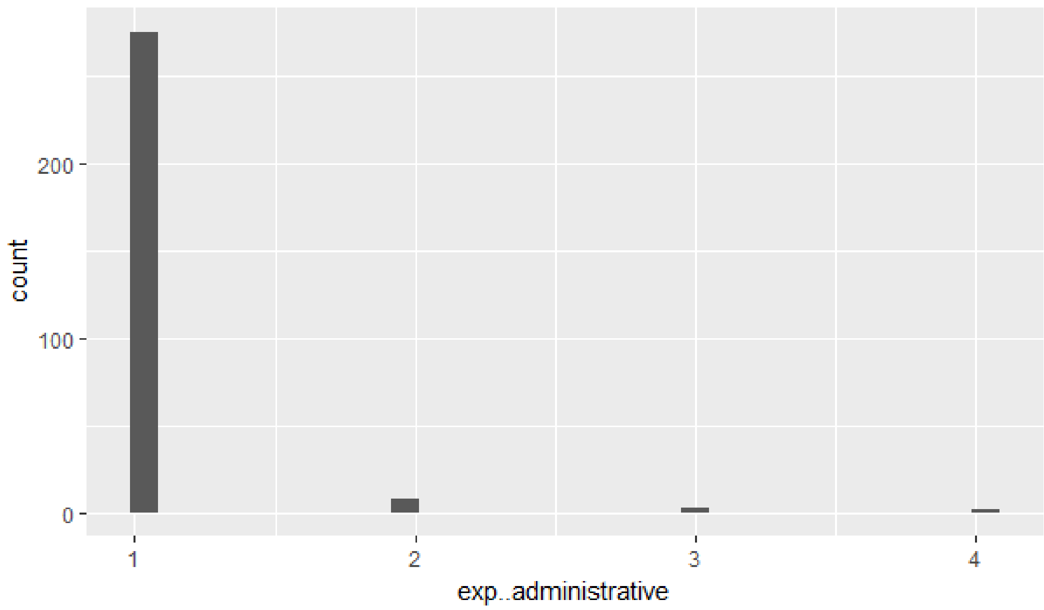
Appendix 8: Frequency of the sample's experiences with m-health technologies for voluntary, thus fitness/wellness purposes



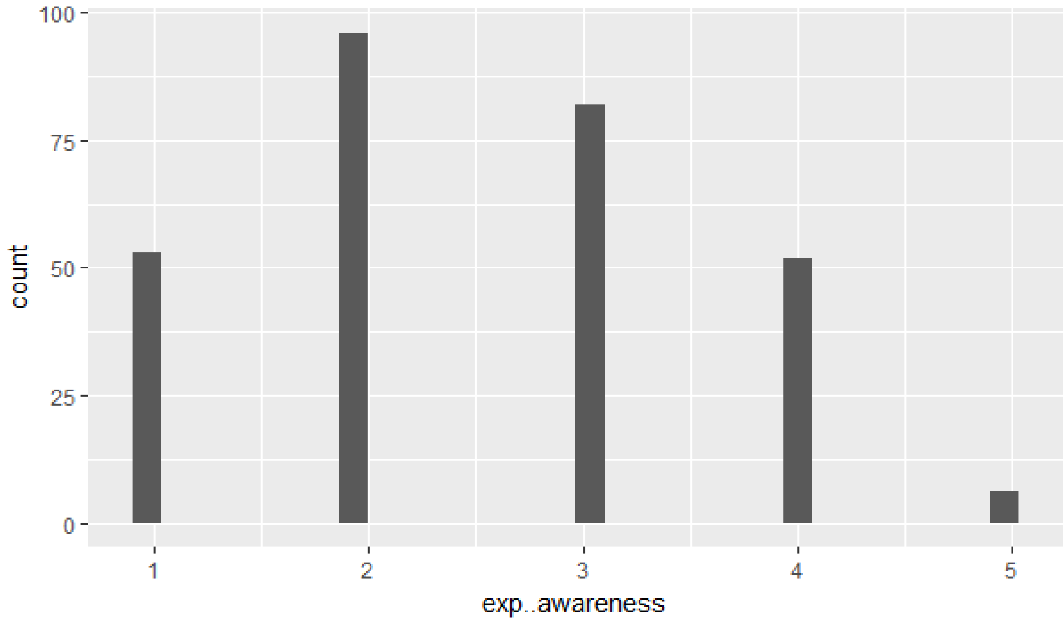
Appendix 9: Frequency of the sample's experiences with m-health technologies for medical purposes



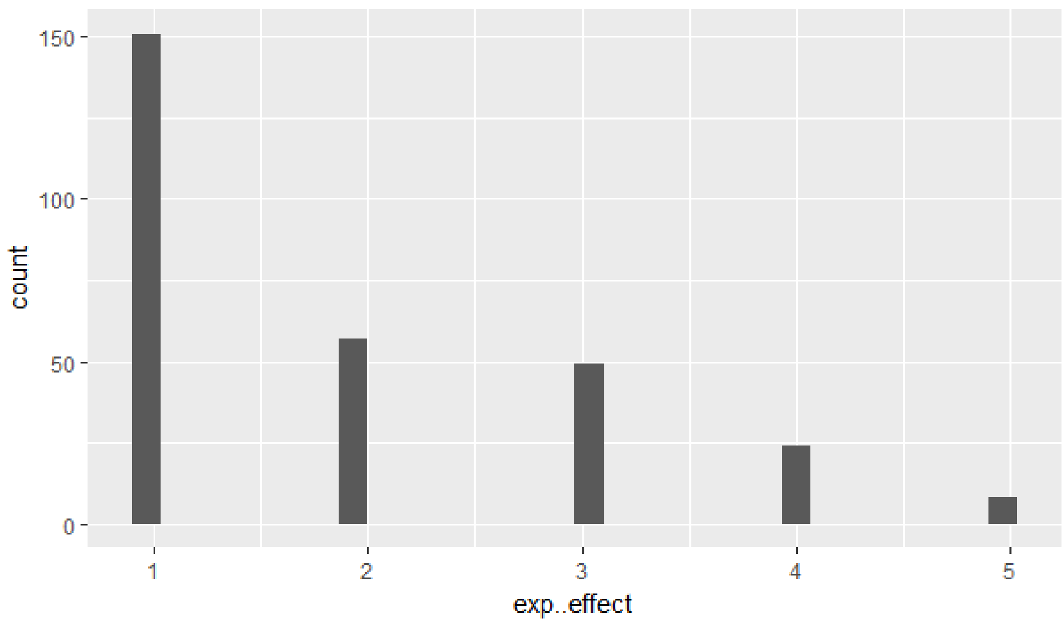
Appendix 10: Frequency of the sample's experiences with m-health technologies for administrative purposes



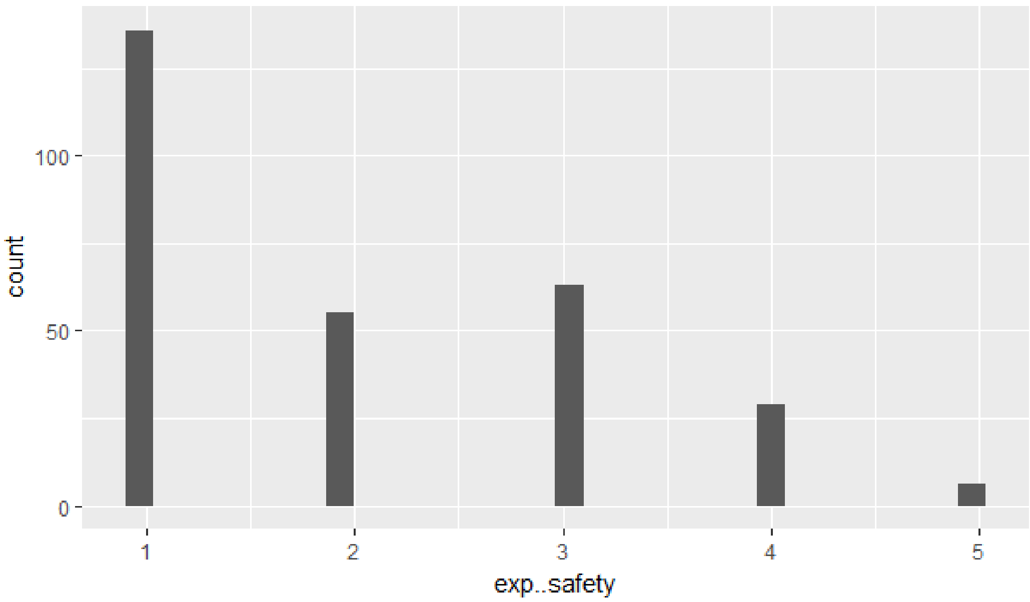
Appendix 11: Sample's perceived awareness of m-health technologies within their social environment



Appendix 12: Sample's perceived effectiveness of using m-health technologies



Appendix 13: Sample's perceived security from using m-health technologies



Appendix 14: Outer Loadings

	BI	EE	FC	PE	PR	PS	SA	SE	SI
BI1	0,942								
BI2	0,933								
BI3	0,952								
EE1		0,905							
EE2		0,887							
EE3		0,896							
EE4		0,851							
FC1			0,516						
FC2			0,717						
FC3			0,916						
PE1				0,870					
PE2				0,819					
PE3				0,843					
PE4				0,901					
PR1					0,470				
PR2					0,870				
PR3					0,950				
PS1						0,750			
PS2						0,630			
PS3						0,767			
PS4						0,770			
PS5						0,837			
PS6						0,728			
SA1							0,846		
SA2							0,856		
SA3							0,749		
SA4							0,900		
SE1								0,933	
SE2								0,931	
SE3								0,912	
SI1									0,952
SI2									0,971
SI3									0,954